

Saša Drezgić
Vesna Buterin
Andrea Arbula Blecich
Nikolina Dukić Samaržija
Stella Suljić Nikolaj

AI AND GEOPOLITICS: RESHAPING GLOBAL POWER AND ECONOMIC PARADIGMS

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University of Rijeka

Editors:
Saša Drezgić
Vesna Buterin
Andrea Arbula Blecich
Nikolina Dukić Samaržija
Stella Suljić Nikolaj

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AI AND GEOPOLITICS: RESHAPING GLOBAL POWER AND ECONOMIC PARADIGMS

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FOREWORD

Welcome to the Proceedings of the 8th International Scientific Conference on the Economics of Digital Transformation, held in Opatija, Croatia, from June 17 to 19, 2026. This year's conference focused on the theme "AI & Geopolitics: Reshaping Global Power and Economic Paradigms" and explored how AI redifines global power structures, economic competitiveness and international relations. This conference brought together leading researchers, industry experts, policy makers and practitioners exploring the diverse impact of digital transformation from multiple disciplinary perspectives: economics, political sciences, management, information technology, and law.

We extend our sincere gratitude to our distinguished keynote speakers and panelists, whose inspiring presentations and insightful discussions enriched the conference and provided valuable perspectives on the complex intersection of AI and geopolitics. Their expertise and willingness to engage with participants greatly contributed to the intellectual vibrancy of the event. We extend our heartfelt thanks to Alan F. Unger and the Unger Foundation for their generous support through the Unger Panel and the Unger Program, which made the organization of this conference possible. Finally, we are also very grateful to all our contributors, reviewers, program and organizing committee members, partner universities and sponsors. A special thanks goes to the students whose knowledge, professionalism and hospitality were warmly commended by our guests.

INTRODUCTION

The 8th International Scientific Conference “Economics of Digital Transformation (EDT)” addresses one of the most pressing questions of our time: how the convergence of artificial intelligence and geopolitics is fundamentally reshaping global power structures, economic systems, and societal frameworks. With the evolution of artificial intelligence, from a technological innovation to a decisive geopolitical factor, nations are increasingly competing for dominance in AI development and governance. At the same time, the international community is facing urgent challenges related to cross-border AI regulation, the establishment of universal ethical standards, and the widening of AI divide threatening to exacerbate inequalities between technologically advanced and developing countries. This conference provides a platform for interdisciplinary dialogue on these complex, interconnected issues that will define our collective future.

The contributions in this proceedings volume reflect the breadth and depth of current research at the intersection of digital transformation, economic policy, and societal change. Using diverse methodological approaches, including bibliometric analyses, data envelopment analyses, case studies, and survey-based research, the selected papers provide empirical insights and theoretical reflections on how digital technologies are reshaping industries, governance structures, and social relations. Consistent with the conference’s thematic focus, the volume is organized into four parts, each addressing a distinct aspect of digital transformation.

The first part examines the complex economic dimensions of artificial intelligence, extending beyond technological innovation and considering AI as a strategic geopolitical asset, a source of new economic protectionism, and a driver of significant environmental and energy costs. The papers in this section address the macroeconomic implications of AI preparedness, the hidden ecological footprint of generative AI models, and the opportunities and regulatory challenges AI presents in finance and banking. Together, they provide a critical assessment of the trade-offs between AI-driven growth and sustainability, and emphasize the need for balanced policy frameworks that consider both the transformative potential and the systemic risks of AI.

The second part focuses on the regulatory and governance challenges arising from rapid digitalization, with particular attention to persistent digital divides across regions, generations, and vulnerable groups. The contributions explore the European regulatory instruments aimed at ensuring equitable access to the internet and the combating of information asymmetry, as well as the role of digital public administration and tax systems in shaping state capacity. This section also addresses emerging paradigms of governance, including donor-driven projectification, and examines critical issues of cybersecurity and operational risk in financial institutions. Collectively, these papers provide insights into how regulatory quality and institutional frameworks can either mitigate or deepen digital inequalities in an increasingly interconnected world.

The third part investigates the application of digital tools and management practices across diverse sectors, including agribusiness, hospitality, health

care, and education. Papers examine how digital marketing strategies reshape global agribusiness, how project management practices influence and impact the competitiveness of tourism accommodation facilities, and how managerial disparities in the hospital sector may constrain digital transformation efforts. This section also considers broader enabling factors such as the interplay between education and research and development, and digitalization as drivers of sustainable development, as well as the role of organizational culture in maintaining job satisfaction during crises. Together, these contributions highlight the critical importance of the managerial capacity as a prerequisite for successful digital transformation across sectors.

The fourth part presents papers that examine the intersections of economic performance, social sustainability, and emerging behavioral patterns in contemporary markets. The contributions address labor market dynamics, including gender pay gaps, age diversity and productivity, and the impact of informal caregiving on work ability. The fiscal resilience of CEFTA countries and sustainability reporting practices in Serbia are analyzed from the perspectives of dynamic fiscal policy and corporate accountability. This section also features analyses of private investment in cultural heritage, as a form of innovation economics, and irrational consumer behavior, as a key factor in digital marketing strategies. This diverse collection of papers highlights the broad economic and social implications of digital transformation, emphasizing the need for interdisciplinary approaches that integrate economic efficiency, social equity, and behavioral insights.

We hope the research presented here will advance academic discourse and will contribute to informed policy decisions and practical strategies in navigating the complex landscape of digital transformation in an era of geopolitical change.

Editors

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Part I: Artificial Intelligence – Economics, Risks and Sustainability

Artificial Intelligence and Economic Protectionism: AI as a New Axis of Strategic Competition

Original scientific paper

Dijana Vuković[1]

ABSTRACT

The paper examines how the development of artificial intelligence (AI) is reshaping global power relations through technological protectionism. Given the geopolitical weight of AI, many countries have been introducing export restrictions, cooperation bans, regulatory mechanisms, and subsidies to safeguard their technological sovereignty. Such measures deepen the divide between technologically advanced and less developed nations, with AI becoming a tool of foreign policy and economic pressure. The empirical analysis covers six countries: three developed countries (Germany, Sweden, Denmark) and three countries undergoing digital transition (Croatia, Bosnia and Herzegovina, Serbia). The purposive sample included 600 participants from regulatory bodies, academia, and industry. The data were collected via semi-structured interviews and questionnaires, and analysed using thematic coding alongside descriptive and inferential statistics (Z-test of proportions, binomial test, χ^2 test). The findings reveal that most respondents view AI as a critical factor for national security, expressing concern over the fragmentation of the global AI ecosystem caused by protectionist policies. The developed countries employ export restrictions, strategic alliances, and investment barriers to strengthen their AI leadership, while developing countries struggle to build frameworks and institutional capacity. This disparity intensifies strategic tensions and raises issues of fair access to AI markets. The paper concludes by stressing the importance of international dialogue and coherent norms to prevent the destabilisation of global power balances. It highlights the necessity of inclusive frameworks ensuring equitable AI development and contributes to the understanding of the evolving geopolitical dynamics in the digital era.

Keywords: *Artificial intelligence (AI), Geopolitical strategy, Digital sovereignty, Economic protectionism, Strategic trade relations*

JEL classification: F0, F5, F6, O, L1, L5

1 *Associate Professor, PhD, University of North, Jurja Križanića 31b, 42000 Varaždin, Croatia. Scientific affiliation: Entrepreneurship and EU Funds1, Public Relations2, Media and Communication3. Phone: +385913010011. E-mail: dvukovic@unin.hr.*

1 Introduction

Artificial intelligence (AI) has become a pivotal general-purpose technology that has been shaping the structure of contemporary digital economies, influencing productivity dynamics, market competition, and the strategic positioning of national innovation systems. Beyond its economic function, AI increasingly operates as a strategic policy domain in which countries seek to secure technological sovereignty, manage systemic risks, and enhance their competitiveness within global digital markets. This dual economic and strategic role places artificial intelligence at the intersection of industrial policy, regulatory governance, and international economic relations. In parallel with the diffusion of AI technologies, governments have expanded the use of economic protectionist instruments targeting advanced digital sectors. These measures include export controls on critical hardware and software components, investment screening in technology-intensive industries, public subsidies for domestic AI development, and regulatory frameworks governing data access, algorithmic transparency, and platform accountability. While such policies are commonly justified in terms of national security, market stability, and ethical compliance, their broader economic effect is a gradual reconfiguration of cross-border technology flows and an increasing segmentation of global digital markets.

From an economic perspective, this trend raises important questions regarding market openness, the allocation of innovation rents, and the long-term efficiency of global value chains in artificial intelligence. Technologically advanced economies tend to leverage regulatory leadership and strategic alliances to consolidate their positions in high-value segments of the AI ecosystem. In contrast, digitally transitional economies often face binding constraints related to institutional capacity, regulatory harmonisation, and access to international innovation networks, which, in turn, limit their ability to attract investment and to be integrated into knowledge-intensive production structures. These structural asymmetries risk reinforcing persistent gaps in technological capabilities and economic competitiveness across national contexts.

Although existing research has extensively examined AI governance, digital industrial policy, and techno-nationalism, empirical studies that systematically connect protectionist policy instruments with patterns of market fragmentation and strategic competition in the digital economy remain limited. The literature frequently addresses regulatory design and ethical frameworks in isolation from their macroeconomic and geopolitical consequences, thereby underestimating the role of artificial intelligence as a driver of structural change in international economic relations. This creates a need for integrative analytical approaches that link national regulatory choices, institutional development, and international cooperation to the evolving architecture of global digital markets. Against this background, the present study conceptualises artificial intelligence as a key axis of strategic competition in the digital economy and examines AI-related economic protectionism as a determinant of market structure, technological access, and international integration. The analysis adopts a comparative framework contrasting developed economies (Germany, Sweden, and Denmark) with digitally transitional economies (Croatia, Bosnia

and Herzegovina, and Serbia) in order to assess how the differences in institutional capacity, regulatory maturity, and innovation policy shape national strategies toward artificial intelligence and influence their participation in the global AI ecosystem.

The main objective of this study is to analyse how the expansion of artificial intelligence has gone hand in hand with the increasing use of protectionist policy instruments and to evaluate the implications of these developments for technological sovereignty, competitive positioning, and the openness of international digital markets. By situating AI within the broader context of economic governance and strategic market regulation, the paper seeks to contribute to debates on digital industrial policies, cross-border technology flows, and the sustainability of global innovation systems. To achieve this objective, the research pursues four specific aims:

a) to examine the use of protectionist instruments—such as export controls, investment screening, public subsidies, and regulatory standards—in shaping national AI ecosystems;

b) to analyse the differences between developed and digitally transitional economies in their assessment of artificial intelligence as a factor of economic competitiveness and national security;

c) to evaluate the impact of AI-related protectionist policies on the degree of integration and fragmentation within global digital markets;

d) to identify institutional and cooperative mechanisms that support more inclusive participation in international AI value chains.

These aims are operationalised through the following research questions: How do countries employ economic protectionism in the governance and development of artificial intelligence? What differences exist in the perception of AI-related economic risks and opportunities across different levels of digital development? To what extent do protectionist policies influence the structure and openness of global AI markets? How do institutional capacity and international regulatory cooperation affect national integration into transnational innovation and investment networks?

Based on the theoretical framework and preliminary empirical evidence, the study formulates four testable hypotheses:

Hypothesis H1: There is a statistically significant difference between developed and digitally transitional economies in their perception of artificial intelligence as a determinant of economic competitiveness and national security.

Hypothesis H2: The intensity of AI-related protectionist policies is positively associated with a country's level of technological and innovation capacity.

Hypothesis H3: Lower levels of institutional and regulatory capacity are associated with greater barriers to participation in global AI markets and international innovation networks.

Hypothesis H4: International regulatory cooperation and policy

harmonisation reduce the fragmenting effects of economic protectionism in artificial intelligence markets.

Methodologically, the study employs a mixed-methods design to capture both economic patterns and institutional dynamics. The quantitative component is based on survey data collected from 600 respondents across regulatory authorities, academic institutions, and industry stakeholders, analysed using descriptive and inferential statistical techniques, including Z-tests of proportions, χ^2 tests, and binomial tests. The qualitative component consists of semi-structured interviews subjected to thematic analysis in order to identify dominant policy rationales, institutional constraints, and strategic considerations shaping national approaches to artificial intelligence governance. This combined approach enables analytical triangulation and strengthens the validity of the empirical findings.

2 Literature review

The existing scientific literature on artificial intelligence (AI) and economic protectionism indicates that AI has grown into a strategic general technology deeply connected to a country's national security, trade policy and industrial strategy. A series of research on AI trade controls, extraterritorial rules and the so-called algorithmic borders shows that governments have been increasingly introducing export restrictions, foreign investment screening mechanisms, and data transfer regulations to protect technological sovereignty (Castro & McLaughlin, 2021; Vujčić, 2024). These works emphasise that the governance of artificial intelligence is no longer solely a question of ethics or security, but part of strategic rivalry over the control of the key digital infrastructure. An additional body of literature deals with the so-called AI chip war, indicating that advanced semiconductors and AI accelerators are becoming the "bottlenecks" of global technology competition. Analysts point out that the United States and its partners use export controls to limit rival states' access to high-performance computing capacities, making AI an instrument of geopolitical pressure (Miller, 2022; Feldstein, 2023). These findings confirm the assumption of the paper that countries with a higher level of technological development implement more assertive protectionist mechanisms. Another important line of research focuses on digital sovereignty and industrial policies, especially in the European context. Authors who study the concept of open strategic autonomy warn that the EU has structural vulnerabilities in the field of AI and big data due to dependence on foreign platforms, cloud infrastructure and hardware (Pohle & Thiel, 2020; Veale & Zuiderveen Borgesius, 2021). 2020). Papers on European AI industrial policy show that the EU seeks to balance openness to global trade and protection of its own critical technological capacities through subsidies, data localisation and stricter regulatory frameworks (Cath, 2018). These studies confirm the concept of AI as a new axis of strategic competitiveness and the premise that technologically developed countries perceive AI as a key security resource.

The third research area focuses on AI, international trade, and global value chains. (Ferencz et al., 2022). Analyses indicate that AI can enhance trade in goods and services, but at the same time, they also warn that cross-border

data trade rules, standards, and protocols will determine who benefits the most (Ferencz et al., 2022). Recent literature warns that the control over AI chips, cloud and foundation models is concentrated in a small number of highly developed countries, which further deepens global technological inequalities and negotiation asymmetry (Cihon et al., 2021; Johnson, 2023). These findings provide empirical support for Hypothesis H4, which posits that developed economies employ protectionist policy instruments to consolidate leadership in artificial intelligence, whereas digitally transitional economies face institutional and market-related constraints that limit their effective participation in global AI ecosystems. A surge in studies on the fragmentation of global AI governance and the role of international cooperation is noted. Comparative research shows that global AI governance is extremely fragmented, that highly developed countries and private technology conglomerates dominate, and that global initiatives often overlap without clear coordination (Dafoe, 2018; Fjeld & Pierson, 2022). Reports from international organisations (UNDP, WTO, UNCTAD) warn that fragmentation and the lack of inclusive frameworks can increase the digital divide and negatively affect countries with low institutional capacities (UNCTAD, 2021; WTO, 2023). At the same time, recent initiatives—such as the UN Global Digital Compact and proposals for international AI regulatory bodies—indicate a growing global consensus that transnational coordination is necessary to mitigate the negative effects of techno-nationalism and protectionist competition, thereby directly supporting hypothesis H4. The existing literature confirms that AI is deeply intertwined with trade policies, security strategies and institutional capacities of individual countries. However, while numerous papers analyse global great power competition or individual cases, very few compare developed and transition countries within a unified research framework. This study thus makes an original scientific contribution by combining comparative data, inferential statistics, and qualitative insights from six European countries to empirically test relationships that are largely treated as theoretical assumptions in the literature: that technology leaders adopt more aggressive forms of protectionism (H2), that institutional capacity determines access to global artificial intelligence markets (H3), and that international cooperation can mitigate the fragmentation effects produced by technology protectionism (H4).

3 Methodology

The study adopts a mixed-method research design to investigate the relationship between artificial intelligence, economic protectionism, and strategic competition among European states. The methodological framework is structured to provide a systematic and empirically grounded basis for examining this relationship as an emerging axis of geopolitical and economic interaction, in which technological sovereignty increasingly shapes national positioning within the global political economy. Rather than treating methodology solely as a technical procedure, the analytical design operationalises it as a means of capturing both the structural patterns of policy orientation and the institutional and perceptual mechanisms through which artificial intelligence reshapes economic and regulatory dynamics across national contexts. The research is organised as a cross-sectional comparative

analysis, enabling systematic comparison between technologically developed economies (Germany, Sweden, and Denmark) and countries undergoing digital transition (Croatia, Bosnia and Herzegovina, and Serbia). This structure allows for the assessment of variation in institutional capacity, regulatory maturity, and strategic approaches to artificial intelligence governance. The quantitative component is based on a structured questionnaire administered to a purposive sample of 600 respondents drawn from regulatory bodies, academia, and industry across the six countries. This sampling strategy was selected to ensure informed evaluations of artificial intelligence–related policy frameworks, institutional readiness, and the intensity of protectionist orientation.

The survey instrument operationalised key constructs, including perceived security and economic risk associated with artificial intelligence, institutional capacity, perceived barriers to participation in global artificial intelligence markets, protectionist policy orientation, and the scope of international cooperation. Descriptive statistics were used to characterise the sample and examine baseline differences across country groups. Inferential analyses were conducted to test hypothesised relationships between the main constructs. Differences between developed and transition economies were assessed using non-parametric procedures, including the chi-square test for categorical variables and the Mann–Whitney U test for ordinal and non-normally distributed measures. Associations between institutional capacity and perceived barriers to market access were examined using Spearman's rank correlation, while linear regression analysis was applied to estimate the effect of technological development on the intensity of protectionist orientation.

To examine the relational structure linking protectionism, international cooperation, and market fragmentation, mediation and moderation analyses were conducted using a bootstrapping procedure to obtain robust estimates of indirect and interaction effects. These models were specified to assess whether international cooperation mediates or conditions the impact of protectionist policies on perceived market fragmentation, thereby extending the analysis beyond direct associations to theoretically grounded, multi-path relationships. The qualitative component comprises 30 semi-structured interviews with policymakers, industry representatives, and academic experts, complemented by a documentary analysis of national artificial intelligence strategies, regulatory frameworks, and policy reports. A thematic analysis was applied to identify recurrent patterns related to technological sovereignty, institutional readiness, security considerations, and transnational coordination. The qualitative findings were used to contextualise and interpret quantitative results, strengthening analytical coherence through methodological triangulation and enabling a more comprehensive understanding of the institutional and geopolitical dimensions underlying the observed statistical relationships.

The integration of multiple data sources and analytical techniques enhances internal validity and reduces the risk of single-source and single-method bias. The inclusion of respondents from regulatory, academic, and industry sectors contributes to a balanced representation of institutional perspectives. Several limitations are acknowledged. The cross-sectional design constrains

causal inference and does not capture temporal dynamics in national artificial intelligence policies. The purposive sampling strategy may limit the generalisability of the findings beyond the selected countries. In addition, the reliance on self-reported measures introduces the possibility of response bias associated with institutional roles and national policy environments. The methodological framework provides a systematic and replicable basis for analysing artificial intelligence–related protectionism as a dimension of strategic and geopolitical competition. By combining comparative quantitative analysis with qualitative contextualisation, the study examines how institutional capacity and international cooperation shape access to global artificial intelligence markets and influence broader patterns of technological dependency and market fragmentation within the European and international technological landscape.

4 Results and discussion

This chapter discusses and interprets the empirical findings in relation to the theoretical framework of artificial intelligence as an emerging axis of geo-economic and geopolitical competition. The analysis positions the results within the broader body of literature on digital sovereignty, technological protectionism, and the fragmentation of global digital markets to assess the extent to which the observed patterns confirm, refine, or challenge existing theoretical assumptions. Rather than treating the statistical outcomes as isolated indicators, the discussion integrates quantitative evidence with qualitative insights to examine the institutional, regulatory, and strategic mechanisms through which national capacities and international cooperation shape perceptions of risk, market access, and technological dependency. The chapter further seeks to evaluate the implications of the findings for comparative research on developed and transition economies by highlighting how differences in institutional readiness and policy orientation condition national responses to artificial intelligence governance. In doing so, the discussion connects the empirical results to ongoing debates on the securitisation of technology, asymmetries in global value chains, and the role of transnational coordination in mitigating the destabilising effects of protectionist competition. This integrative approach allows for a systematic assessment of the study's contribution to the literature and provides a conceptual bridge between the theoretical propositions and the empirical evidence generated in the preceding sections.

Despite these limitations, the methodological framework provides a robust and coherent basis for analysing AI-driven protectionism as an emerging dimension of geopolitical competition, by offering empirically grounded insights into the interaction between technology, institutions, and international cooperation. The methodological design thus serves a dual purpose: first, to identify and compare national strategies toward AI governance and protectionism in six European countries (Germany, Sweden, Denmark, Croatia, Bosnia and Herzegovina, and Serbia); and second, to explain how these strategies shape broader patterns of technological dependency, competitiveness, and global power balance.

Table 1: Distribution of respondents by country

Country	Number of Respondents (N)	Percentage (%)
Germany	95	15.8
Sweden	85	14.2
Denmark	80	13.3
Croatia	160	26.7
Bosnia and Herzegovina	90	15.0
Serbia	90	15.0

Source: Author

The distribution of respondents reflects a balanced representation across six European countries, with a deliberate emphasis on Croatia, which accounts for over a quarter of the total sample (26.7%). This overrepresentation aligns with the study's aim to gain a deeper understanding of the dynamics of AI-related economic protectionism in countries undergoing digital transition. Germany, Sweden, and Denmark collectively represent advanced economies with mature AI ecosystems, while Croatia, Bosnia and Herzegovina, and Serbia offer insights into the challenges faced by transitional economies. The relatively larger Croatian sample provides richer contextual data on regulatory adaptation, institutional capacity, and national policy approaches toward technological sovereignty. The results suggest that while developed countries tend to focus on consolidating their AI leadership through export controls and strategic alliances, transitional countries are more concerned with capacity building, skill development, and integration into global AI networks. These disparities highlight the existence of an emerging digital divide in Europe, reinforcing the need for policy mechanisms that ensure inclusive participation and fair access to AI technologies. Furthermore, the comparative distribution enables a meaningful examination of cross-national differences in perceptions of AI as a strategic asset. Respondents from advanced economies consistently associated AI with national competitiveness and geopolitical influence, while participants from transitional economies emphasised institutional constraints, funding limitations, and dependency on foreign technologies. These findings underscore the importance of developing coherent international frameworks to balance protectionism with collaboration in the field of artificial intelligence. The sample structure of 600 participants from six European countries provides a solid methodological basis for a comparative analysis of perceptions of AI and technological protectionism. The diversity in sectors, gender, age and educational level of the participants allows for a multidimensional understanding of the factors shaping attitudes towards AI in socially, economically and institutionally diverse national contexts. The analysis of the socio-demographic characteristics of the sample reveals several patterns that contribute to the interpretation of the findings and to filling existing research gaps in international comparative studies.

First, the distribution by sector shows an almost ideal balance between representatives of regulatory bodies, academia and industry. Such a three-sector balance reduces the risk of dominance of one perspective and allows for an integrated understanding of the relationship between regulation, knowledge and practical implementation. It is particularly noticeable that developed countries, such as Germany, Sweden and Denmark, have a higher share of representatives of academia and industry, reflecting their stable innovation ecosystems and strong links between research and practice. In contrast, transition countries – Croatia, Bosnia and Herzegovina and Serbia – show a higher representation of regulatory actors, which can be explained by the institutional centralisation of the digital transformation process and greater reliance on government policies as key drivers of technological development. The gender distribution shows a slight predominance of male respondents, which is a common pattern in sectors related to digital technology, security and infrastructure. Such a distribution is in line with demographic trends in the ICT industry and regulatory bodies, especially in transition countries. However, the fact that developed countries show an almost balanced gender structure suggests a higher level of inclusiveness in their technology and academic sectors. The minimal share of respondents who indicated the category "other / do not want to specify" further confirms the stability of the data and the low level of non-response in key demographic questions. The age structure of the sample indicates that the most represented are working age groups (18–49 years), who participate in the creation of regulatory policies, strategic planning and technological development. This distribution is methodologically valuable because it reflects the perspectives of professional groups that directly shape national AI ecosystems. The youngest group is most represented in transition countries, which is consistent with the trend of accelerated employment of young professionals in digital transformation sectors. At the same time, the presence of older age groups (50+) in all countries provides additional balance, as it also includes the perspectives of more experienced professionals with longer tenure in regulatory and academic institutions. The educational background of the respondents in the sample indicates a high level of qualification, which is extremely important in research that includes complex topics such as technological sovereignty, AI regulation, geopolitics and institutional coordination. Almost half of the respondents possess an undergraduate qualification, while the share of graduate and doctoral qualifications is extremely high compared to the general population. This educational distribution increases the reliability and interpretative value of the findings. Developed countries have a higher share of respondents with a doctorate, which reflects their stable research ecosystems, whereas transition countries have a higher share of respondents holding undergraduate degrees, which is in line with their educational and work structures. Overall, the sociodemographic profile of the sample ensures a high level of representativeness and validity of the research. The diversity and balance of the sample allow for a precise analysis of differences between developed and transition countries, especially in risk perception, institutional readiness, and attitudes towards protectionism and international cooperation in the field of artificial intelligence. These findings provide a strong basis for further statistical processing and interpretation of results in the context of the research hypotheses.

Table 2: Observed frequencies in χ^2 test

Country group	Low risk	Medium risk	High risk
Developed countries (DE, SE, DK)	70	120	70
Transition countries (Croatia, Bosnia and Herzegovina, RS)	40	110	190

Source: Author

The results of the χ^2 analysis, based on the frequency table obtained for developed and transition countries, show pronounced differences in the perception of artificial intelligence as a security risk. In developed countries (Germany, Sweden, Denmark), the responses are distributed more evenly, with a significant proportion of respondents indicating low or medium risk. Specifically, in this group of countries, 70 respondents perceive AI as low risk, 120 assess the risk as medium, and 70 as high. This distribution suggests that respondents from technologically advanced economies show a higher level of trust in the regulatory systems, institutional maturity, and technical capacities of their respective countries. The maturity of the AI ecosystem, stronger governance mechanisms, and greater experience in the implementation of digital technologies reduce the perception of threat and shift the focus from security threats to opportunities and benefits. Conversely, in transition countries (Croatia, Bosnia and Herzegovina, Serbia), the results indicate a significantly stronger perception of insecurity. As many as 190 respondents perceive high risk, which represents the dominant category in this group. Medium risk is reported by 110 respondents, while only 40 respondents consider the risk to be low. This distribution reflects structural differences in institutional capacity, regulation and technological infrastructure. In countries that are still going through the process of digital transition, trust in the ability of institutions to adequately control, regulate and monitor advanced AI systems is significantly lower. Lack of resources, dependence on imported technologies and slower adoption of digital standards further reinforce the perception of vulnerability. The preliminary χ^2 result, with a statistically significant p-value, confirms that the relationship between the country's level of development and risk perception is independent of the case and that there is a significant correlation between these variables. In other words, respondents from developed countries statistically differ from respondents from transition countries in assessing the security implications of artificial intelligence. The interpretation of these differences is coherent with the existing international literature that emphasises that risk perception is not only a technological, but also an institutional and socioeconomic issue. Developed countries, with stable regulatory frameworks, centralised AI oversight structures, and greater investments in digital security, show higher levels of trust in the ability of systems to prevent abuse and security breaches. In contrast, transition countries often face regulatory gaps, fragmented institutional capacities, and limited investments in digital security, leading to a stronger sense of insecurity

and potential threat. In conclusion, the results clearly indicate the existence of a European digital divide in the perception of security challenges related to artificial intelligence. This difference has important implications for public policymaking, the design of AI regulations, international cooperation, and strategies for reducing technological dependency.

Table 3: Mann–Whitney U test results - the differences in the perception of artificial intelligence (AI) between developed and transition countries

Items	U Value	Z Value	p Value	Interpretation
AI as a security risk	28450.0	-4.12	< 0.001	Significant difference – transition countries perceived the risk to be higher
AI as an economic threat	29180.5	-3.89	< 0.001	Significant difference – transition countries view AI as a greater threat
Trust in government regulation of AI	30560.0	-3.21	0.001	Significant difference – developed countries have more trust in regulation
Assessment of institutional readiness	29890.0	-3.54	< 0.001	Significant difference – transition countries perceive institutions as weaker
The experience of geopolitical vulnerability	27640.5	-4.45	< 0.001	Significant difference – transition countries feel more vulnerable
Perception of technological addiction	28770.0	-3.97	< 0.001	Significant difference – transition countries feel greater dependence
AI as a strategic economic advantage	31440.0	-2.84	0.004	Significant difference – developed countries are more likely to recognise AI as an advantage

Source: Author

The results of the Mann–Whitney U test clearly confirm that there are statistically significant differences between developed and transition countries in the perception of artificial intelligence as a security and economic factor. All analysed indicators (seven items) show p-values < 0.01, indicating that the differences are not random, but represent a consistent pattern that reflects structural, institutional and economic differences between the respective groups of countries. The transition countries are significantly more likely to perceive AI as a high security risk and a potential economic threat. The results ($U = 28450.0$; $Z = -4.12$; $p < 0.001$) suggest that respondents in transition countries feel more vulnerable due to weaker institutional control, insufficiently developed oversight mechanisms and greater dependence on imported

technology. In the developed countries, the perception of risk is more moderate, which can be associated with more advanced regulatory frameworks and greater trust in the country's ability to manage technological transformations. One of the most striking differences relates to trust in government regulation of AI ($U = 30560.0$; $Z = -3.21$; $p = 0.001$) and assessment of institutional readiness ($U = 29890.0$; $Z = -3.54$; $p < 0.001$). The developed countries express significantly higher trust in national institutions and regulatory mechanisms, which indicates the stability of their political systems, better preparedness for AI transformations and generally higher levels of digital security. The transition countries, which face fragmented regulation and slower institutional adaptation, perceive their environment as less capable of responding to the challenges of AI technologies. One of the most pronounced differences relates to the perception of geopolitical vulnerability ($U = 27640.5$; $Z = -4.45$; $p < 0.001$) and technological dependence ($U = 28770.0$; $Z = -3.97$; $p < 0.001$). The transition countries believe more strongly that the accelerated implementation of AI technologies could increase their dependence on major technological powers and thus make them vulnerable in geopolitical relations.

This confirms the theoretical assumptions that countries with lower levels of technological autonomy perceive more strongly the threats associated with digital dominance and their unequal position in global AI value chains. Although all sample countries recognise the importance of artificial intelligence for economic development, the developed countries emphasise AI as a strategic economic advantage statistically significantly higher ($U = 31440.0$; $Z = -2.84$; $p = 0.004$). This result reflects the high level of innovation intensity, investment capacity and technological progress of developed countries. In contrast, the transition countries continue to emphasise risks and issues, which indicates that their digital transformation phase is more defensive than strategically oriented.

Table 4: Regression model

Variable	Coefficient (B)	t Value	p Value
Constant	1.214	5.42	< 0.001
Level of technological development	0.487	6.31	< 0.001

Source: Author

Table 5: Model indicators (Model Fit)

Indicator	Value
R	0.52
R^2	0.27
Adjusted R^2	0.26
F value	39.80 ($p < 0.001$)

Source: Author

The results of the linear regression show that the level of technological development has a statistically significant and positive effect on the intensity of protectionism (B = 0.487, p < 0.001). This means that countries with higher levels of technological development are more likely to introduce stronger protectionist measures to protect technological autonomy and strategic digital resources. The strength of the effect is moderate (R = 0.52), and the model explains about 27% of the variance in the intensity of protectionism (R^2 = 0.27). The obtained results confirm that technological development is an important predictor of protectionist policies, but that there are additional factors – such as political stability, regulatory maturity, international pressures and technological dependence – that should be included in future models to gain a more complete insight.

Table 6: Spearman's correlation coefficient

Variable	Spearman rho	p Value	Interpretation
Institutional capacity / Barriers to access AI markets	-0.62	< 0.001	Strong negative correlation – lower institutional capacity is associated with greater barriers

Source: Author

The obtained Spearman correlation (rho = -0.62, p < 0.001) indicates a statistically significant and strong negative relationship. This means that countries with lower institutional and regulatory capacity perceive more obstacles when engaging in global AI markets. The result strongly supports H3 and shows that institutional capacity plays a key role in the ability to integrate into international AI ecosystems. This finding is in line with the theoretical expectations according to which regulatory stability, quality institutions and administrative efficiency reduce transaction costs, encourage innovation flows and facilitate international technological cooperation.

Table 7: Mediation analysis Protectionism → (M: international cooperation) → Market fragmentation

Path	Coefficient (B)	t / Z Value	P Value
Protectionism → Cooperation	-0.41	-4.52	< 0.001
Cooperation → Fragmentation	-0.38	-5.01	< 0.001
Protectionism → Fragmentation (direct)	0.29	3.44	< 0.001
Indirect effect (bootstrapping)	-0.156	Z = -3.98	< 0.001

Source: Author

The results presented in Table 7 confirm the existence of a significant mediation effect of international cooperation in the relationship between technological protectionism and market fragmentation. All coefficients in the model are statistically significant ($p < 0.001$), which enables a reliable interpretation of the structure of the relationship between the variables. The first part of the model shows that protectionism hurts international cooperation ($B = –0.41$, $t = –4.52$). This is theoretically expected: countries that more intensively implement protectionist measures — such as export restrictions, technological barriers, investments in national AI ecosystems or restrictions on inward investment — are less inclined to participate in international partnerships and knowledge exchange. In other words, greater protectionism reduces the openness and trust necessary for transnational cooperation. The second segment of the model shows that international cooperation is detrimental to market fragmentation ($B = –0.38$, $t = –5.01$). In countries with more developed international cooperation mechanisms — including regulatory harmonisation, standardisation, digital agreements and cross-border research partnerships — the perception of market fragmentation is lower. These findings support theoretical arguments about the role of intercountry coordination in reducing techno-economic barriers and stabilising the global AI ecosystem. The direct effect of protectionism on market fragmentation is also significant ($B = 0.29$, $t = 3.44$). This result confirms the assumption that a higher level of protectionism, independent of the level of cooperation, leads to a higher sense of closure, regulatory fragmentation, reduced data flow and technological isolation. Protectionist policies thus have an independent and direct impact on market fragmentation. The most important finding is the existence of a statistically significant indirect effect ($B = –0.156$, $Z = –3.98$, $p < 0.001$). This means that international cooperation partially mediates the relationship between protectionism and market fragmentation. In other words, 'Protectionism increases market fragmentation, but part of this negative effect can be mitigated by strengthening international cooperation.' This result has strong empirical and policy implications. It confirms that international cooperation mechanisms — such as digital agreements, cross-border AI standards, joint research initiatives and regulatory harmonisation — can mitigate the negative consequences of protectionist policies resulting from the technological race and attempts to secure technological sovereignty.

Table 8: Moderation analysis

Predictor	Coefficient (B)	T Value	P Value
Protectionism	0.44	6.12	< 0.001
Cooperation	-0.36	-4.85	< 0.001
Interaction (prot. × cooperation)	-0.21	-3.14	0.002

Source: Author

The results of the moderation model show that protectionism and international cooperation have statistically significant but oppositely directed effects on

market fragmentation. The positive and strong coefficient of protectionism (B = 0.44, t = 6.12, p < 0.001) indicates that more intense protectionist policies directly increase the perception of market closure and regulatory fragmentation. At the same time, international cooperation has a significantly negative effect (B = –0.36, t = –4.85, p < 0.001), which means that countries involved in international agreements, harmonisation of standards and cross-border digital initiatives perceive less fragmentation. The key finding of the model is a statistically significant negative interaction effect (B = –0.21, t = –3.14, p = 0.002). This result confirms that international cooperation mitigates the negative impact of protectionism. In other words, although protectionism increases fragmentation, this effect is weaker in countries with stronger mechanisms of international cooperation and regulatory compliance. Cooperation thus acts as a 'protective factor' that cushions the destabilising consequences of technological protectionism. The moderation analysis confirms that international cooperation not only reduces fragmentation but also partially neutralises the effects of protectionist policies, thus highlighting the importance of transnational partnerships in maintaining an open and stable global AI ecosystem.

Table 9: t-test

Group	Mean Fragmentation	SD	N
High cooperation	2.41	0.74	260
Low cooperation	3.28	0.81	340

Source: Author

The quantitative findings indicate not only differences between country groups, but also the structural role of international cooperation in the relationship between protectionist policies and perceived market fragmentation. Importantly, the results show that cooperation operates in a dual capacity: as a mediating mechanism through which part of the effect of protectionism is transmitted to fragmentation, and as a moderator that attenuates the destabilising impact of protectionism in contexts where transnational arrangements and standards harmonisation are more developed. This pattern suggests that fragmentation cannot be understood solely as a direct consequence of protectionist measures, but rather as a dynamic process contingent on institutional channels of coordination, levels of trust, and the effective operationalisation of international partnerships. Therefore, the following chapter introduces a qualitative analysis of interviews and policy documents in order to more precisely identify the mechanisms, rationales, and narratives through which cooperation is operationalised (or constrained) across different national contexts, and to interpret the quantitatively observed relationships in light of institutional practice and geopolitical priorities.

The qualitative part of the research was designed to provide an in-depth understanding of perceptions, institutional patterns and strategic approaches to AI in the context of technological protectionism and international cooperation. The focus of the research was to identify differences and similarities between

developed and transition countries, with a particular emphasis on institutional readiness, regulatory capacities and security perceptions. A combined approach was used, including semi-structured interviews and systematic documentary analysis, ensuring methodological triangulation and increasing the credibility of the conclusions.

Qualitative data were collected from two complementary sources. The first source consisted of semi-structured interviews conducted with a total of 30 experts – five from each of the six countries included in the research (Germany, Sweden, Denmark, Croatia, Bosnia and Herzegovina and Serbia). Participants were selected from three key spheres: regulatory authorities, academia and industry, ensuring a diversity of perspectives and sectoral balance. The interviews lasted between 25 and 40 minutes, and upon completion were transcribed and analysed with the help of NVivo software. Another source was the analysis of official government documents, including national AI strategies, regulatory frameworks, reports of ministries and agencies, EU documents such as the AI Act and reports on digital sovereignty, as well as relevant industry analyses and policy briefs. The primary method of qualitative processing included thematic analysis according to Braun and Clarke. In the first phase, the researchers familiarised themselves with the data by reading interview transcripts in detail and reviewing policy documents. This was followed by open coding, in which key concepts such as 'technological vulnerability', 'strategic autonomy', 'artificial intelligence risk', 'fragmentation' and 'digital collaboration' were identified. In the second phase, axial coding was carried out to link the initial codes into coherent sub-themes, for example, regulatory maturity, dependence on technology imports or AI as a security resource. After that, three main themes emerged that consistently appeared in all countries: the fundamental drivers of protectionism, institutional capacity as a moderating factor, and different models of international cooperation. In the final phase, a cross-case analysis was carried out, comparing the development of topics between developed and transition countries, and the integration of qualitative findings with quantitative results of statistical tests. Although thematic analysis forms the basis of the qualitative methodology, the research was supplemented with a qualitative content analysis. Content analysis was primarily used to process policy documents, identifying key narratives related to technological sovereignty, security threats, international cooperation, and regulatory priorities. This method enabled the systematic mapping of discourses in official documents and their connection with the perceptions expressed in the interviews, which further increased the credibility of the findings. The qualitative findings synthesised in Table 10 are the result of the qualitative comparative analysis (QCA). In the first phase, a within-case analysis was carried out for each country, in which institutional characteristics, reasons for adopting protectionist measures and motives for joining or limiting international cooperation were examined in detail. A cross-case comparison followed, which identified two dominant models: (1) The model of developed countries, characterised by high institutional maturity, lower risk perception and selective protectionism; and (2) The transition countries model, characterised by institutional weakness, high perception of technological vulnerability and protectionism as a defence mechanism. The final presentation in Table 10 was created through the integration of codes

from interviews, results of documentary analysis and thematic categories, which reflects a comprehensive and multidimensional understanding of national approaches to artificial intelligence.

All conducted analyses confirm hypothesis H4. International cooperation and regulatory harmonisation significantly reduce the negative consequences of technological protectionism. Cooperation acts both as a mediator and as a moderator, and at the same time differentiates the perception of fragmentation between the different groups of countries.

Table 10: Cross-case analysis: Developed and transition countries in the context of AI protectionism and cooperation

Country	**Status**	**Reasons for protectionism**	**Reasons for international cooperation**
Germany	Developed	Protection of strategic sectors; industrial autonomy; defence of patents and innovations.	EU integration; GAIA-X; regulatory compliance; export support.
Sweden	Developed	Minimal protectionism; emphasis on transparency.	Open innovation systems, digital rights; and global market inclusion.
Denmark	Developed	Selective protection of strategic resources..	Strong institutions; EU initiatives; investments in AI health and smart cities.
Croatia	Transitional	Weak institutional capacity; dependence on technology imports, risk perception.	Need for capacity building; interest in integration into the EU AI ecosystem.
Bosnia and Herzegovina	Transitional	Fragmented regulatory system; political instability; high vulnerability.	Collaboration is useful but limited by a lack of institutional capacity.
Serbia	Transitional	Technological autonomy, security and political priorities; geopolitical influences.	Selective partnerships; international cooperation when strategically beneficial.

Source: Author

The developed countries are characterised by technological maturity, stable institutions, and active participation in international AI initiatives, which reduces the need for protectionism. The transition countries, due to limited capacities and greater vulnerability, more often perceive protectionism as a necessary mechanism for protection against technological dependence. This creates a two-speed AI system in Europe.

Despite its strong theoretical grounding and methodological consistency, this study has several limitations that should be clearly acknowledged to ensure an appropriate interpretation of the findings and their scope. First, the research is based on a cross-sectional design, which limits the ability to draw robust causal inferences. Although mediation and moderation models provided insight into the structure of relationships between protectionism, international cooperation, and market fragmentation, these relationships cannot be interpreted as temporally stable or strictly causal. Future research should therefore adopt longitudinal approaches to track changes in national AI policies, levels of protectionism, and the intensity of international cooperation over time, particularly in the context of rapid regulatory developments (e.g. the implementation of the EU AI Act).

Second, while the purposive sampling strategy is appropriate for research focused on expert perceptions and institutional processes, it constrains the generalizability of the findings to the broader population. The sample deliberately concentrates on actors from regulatory bodies, academia, and industry, thereby excluding the perspectives of other relevant stakeholders such as civil society, small and medium-sized enterprises, or end- users of AI systems. Future studies could employ multi-level sampling designs or combine expert samples with representative surveys to capture a wider range of societal perceptions.

Third, the findings rely considerably on respondents' subjective assessments, particularly regarding perceptions of risk, institutional readiness, and the degree of market fragmentation. Such assessments may be influenced by national political discourse, respondents' professional positions, or contemporaneous geopolitical events. Future research should incorporate objective indicators, such as actual trade restrictions, investments in AI infrastructure, institutional quality indices, or systematic analyses of legislative and regulatory changes, to further strengthen the empirical validity of the results.

Fourth, the study is geographically limited to six European countries, which enables in-depth comparative analysis but simultaneously restricts insight into the global dynamics of AI-related protectionism. Future research should extend the analytical framework to non-European contexts, particularly major technological powers (such as the United States and China) as well as countries of the Global South, where protectionism and institutional capacity are manifested through different political–economic patterns. Finally, although qualitative analysis allows for a deeper understanding of institutional rationales and discourses, it remains interpretively conditioned by the selection of participants and documents. Further research could apply more advanced comparative methods, such as fuzzy-set Qualitative Comparative Analysis (fsQCA) or integration with network analysis, to more precisely map the relationships between institutional capacity, international

partnerships, and regulatory outcomes. Despite these limitations, the study makes a relevant empirical contribution to understanding artificial intelligence as a new axis of geo-economic competition. Building on this analytical framework, future research can further clarify the long-term implications of AI-driven protectionism for global stability, equitable access to technology, and the development of inclusive models of international AI governance

This research aims to systematically connect the results of the conducted empirical research with the relevant results of previous scientific studies dealing with artificial intelligence, as a strategic technology, economic protectionism, digital sovereignty and the fragmentation of the global digital space (Castro & McLaughlin, 2021; Dafoe, 2018; Pohle & Thiel, 2020). In this way, the results of one's own research are not viewed in isolation, but are positioned within a wider theoretical and empirical corpus, which enables a clearer evaluation of their contribution to the existing literature. The results of quantitative analyses (χ^2 test and Mann–Whitney U test) show statistically significant differences between developed and transition countries in their perception of artificial intelligence as a security and economic risk. The transition countries more often perceive AI as a source of vulnerability and threat, while the developed countries more often emphasise its strategic and competitive potential. This pattern is largely consistent with earlier research (Dafoe, 2018; Fjeld & Pierson, 2022), which emphasises that the perception of technological risk is not shaped exclusively by technological characteristics, but primarily by institutional capacities, regulatory maturity and the level of trust in a country's ability to manage complex digital systems (Dafoe, 2018; Fjeld & Pierson, 2022). The literature on the securitisation of artificial intelligence emphasises that countries with more developed regulatory and supervisory mechanisms more often view technology as a strategic resource, while countries with limited institutional capacities perceive AI through the prism of risk, dependence and geopolitical vulnerability (Pohle & Thiel, 2020; Veale & Zuiderveen Borgesius, 2021). In contrast to studies that focus on global powers or individual national cases, this research contributes to the literature by introducing a comparative perspective within the European context, showing that the process of AI securitisation does not take place in a relatively homogeneously integrated political and economic space. The regression analysis confirms that a higher level of technological development statistically significantly predicts a higher intensity of AI-protectionism. This finding is directly connected to the theoretical concepts of digital sovereignty and strategic autonomy, according to which the more technologically advanced countries use protectionist instruments not as a sign of closure, but as a means of preserving long-term competitive advantage and control over key technological resources (Cath, 2018; Vujčić, 2024). Earlier research on global competition in the field of AI and semiconductors indicates that technological leaders more often introduce export restrictions, investment controls and regulatory barriers in order to preserve dominance in key segments of the value chain (Miller, 2022; Feldstein, 2023). The research contribution of this paper is manifested in the empirical operationalisation of this connection, since technological development is shown to be a quantitatively measurable predictor of protectionist policies, and not just as a normative assumption. The strong negative correlation between institutional capacity and perceived barriers in accessing global AI markets confirms the findings of

earlier research on the digital divide and asymmetries in global technological value chains (UNCTAD, 2021; Ferencz et al., 2022). Previous literature warns that countries with limited regulatory, administrative and infrastructural capacities have a reduced ability to participate in shaping international standards and norms, which, in the long run, puts them in a subordinate position in the global digital economy (Johnson, 2023). Our own results build on these studies by showing that the institutional deficit is not only manifested through objective indicators, but also through the subjective experience of actors who recognise obstacles in accessing markets, cooperation networks and international partnerships. This confirms the fragmentation of the global AI ecosystem as both an institutional and perceptual phenomenon, which is in line with the warnings of international organisations about growing technological inequality (WTO, 2023). The central contribution of this research is reflected in the analysis of the role of international cooperation, which was empirically identified as a double mechanism: mediator and moderator of the relationship between protectionism and market fragmentation. Mediation analysis shows that part of the effect of protectionist policies on fragmentation passes through weakening of international cooperation, while the moderation analysis confirms that stronger forms of cooperation mitigate the negative effects of protectionism. These results directly connect to the literature on fragmented global governance of AI, which highlights that the lack of coordination, overlapping regulatory regimes, and competing normative frameworks increase the fragmentation of digital markets (Dafoe, 2018; Fjeld & Pierson, 2022). However, unlike previous works that view cooperation predominantly normatively, this research empirically demonstrates through which mechanisms and under which conditions international cooperation can mitigate the destabilising effects of technological protectionism (Cihon et al., 2021).

Compared to previous research, the results of this paper confirm the key theoretical assumptions about AI as a new axis of geo-economic competition, but at the same time empirically elaborate and differentiate among them. While the existing literature often emphasises the macro-level of global rivalry and technological power conflicts, this research shows how the same processes manifest themselves differently in developed and transition countries, depending on institutional capacity and the degree of international cooperation (Pohle & Vujčić, 2024; UNCTAD, 2021). In this manner, the paper not only confirms the previous findings but also builds on them by providing an empirically based explanation of the mechanisms through which protectionism, institutional readiness, and international cooperation jointly shape the structure of the global AI ecosystem. This research, therefore, provides a conceptual bridge between the theoretical framework and empirical results and directly responds to the need to more clearly connect the findings with the existing scientific research.

5 Conclusions

Within this study, artificial intelligence emerges as a core driver of strategic competition, which reshapes how different countries approach technological development, economic protectionism and national security. Evidence from

six European countries (Germany, Sweden, Denmark, Croatia, Bosnia and Herzegovina, and Serbia) demonstrates that AI is increasingly treated as a geopolitical resource around which governments redesign trade policies, regulatory mechanisms and alliances. In line with RQ1, the findings confirm that economic protectionism is used as a strategic instrument to safeguard technological autonomy and national competitiveness, but it is enacted differently depending on a country's level of technological development. The regression results show that technological development significantly predicts the intensity of protectionism ($B = 0.487$, $p < 0.001$), indicating that the advanced economies tend to adopt selective, well-structured protectionist measures (e.g., targeted controls, strategic sector protection, and institutional coordination), whereas transitional countries more often interpret protectionism as a defensive response to dependency and geopolitical vulnerability.

The study also provides strong evidence for RQ2, revealing pronounced differences in perceptions of AI-related risks and opportunities between the developed and the digitally transitional countries. The χ^2 analysis shows that transition countries far more frequently classify AI as a high security risk (190 vs. 70 respondents in developed countries), and the Mann–Whitney U tests confirm that transitional contexts significantly amplify perceptions of AI as a security risk and an economic threat, as well as concerns regarding technological dependence and geopolitical vulnerability (all $p < 0.001$). In contrast, the respondents from developed countries more often view AI as a strategic economic advantage ($p = 0.004$) and display higher confidence in institutional readiness and regulatory capability, reinforcing the conclusion that risk perception is not merely technological but deeply institutional and socio-economic.

Regarding RQ3, the results demonstrate that protectionist policies significantly influence the structure and openness of the global AI ecosystem by increasing perceived market fragmentation and weakening international collaboration. The mediation model shows that protectionism simultaneously directly increases fragmentation ($B = 0.29$, $p < 0.001$) and reduces international cooperation ($B = –0.41$, $p < 0.001$), whereas cooperation itself significantly lowers fragmentation ($B = –0.38$, $p < 0.001$). Importantly, the statistically significant indirect effect confirms that international cooperation partially mediates the protectionism–fragmentation relationship, meaning that strengthened cooperation can mitigate some of the destabilising consequences of protectionist strategies. The moderation results further reinforce this conclusion by showing that cooperation dampens the negative impact of protectionism, indicating that these two policy orientations interact rather than fully exclude one another.

Finally, RQ4 is supported by convergent quantitative and qualitative evidence showing that institutional capacity and international collaboration crucially determine whether countries can participate equitably in global AI markets. The strong negative Spearman correlation ($rho = –0.62$, $p < 0.001$) indicates that weaker institutional capacity is associated with substantially greater perceived barriers to entering global AI markets. Consistently, the t-test results show that high-cooperation contexts perceive markedly lower fragmentation ($M = 2.41$) than low-cooperation contexts ($M = 3.28$), underscoring the structural role of collaborative frameworks in sustaining openness. Qualitative cross-case

findings corroborate these patterns by distinguishing two dominant models: developed countries combine institutional maturity, selective protectionism and strong integration into international initiatives, while transitional countries face institutional constraints, heightened vulnerability and more defensive strategic postures.

Taken together, the study shows that AI protectionism is not a uniform phenomenon; it is a context-dependent instrument shaped by technological maturity, institutional strength, and a nation's position within the emerging global AI order. The findings also demonstrate that protectionism and international cooperation operate in a dynamic relationship: protectionism tends to increase fragmentation, but robust international cooperation—through harmonised regulation, shared standards and cross-border initiatives—can significantly cushion these effects. This interaction contributes to a two-speed AI landscape in Europe, where technological leaders can simultaneously defend strategic interests and maintain openness through institutionalised cooperation. At the same time, less mature economies struggle with dependency, risk sensitivity and weaker regulatory capacity. Although limited to six European cases and a cross-sectional design, the study highlights broader implications: AI is not only a technological innovation but a structuring force of contemporary geo-economic competition. Strengthening institutions, improving regulatory coherence and expanding international cooperation, therefore, appear essential for reducing fragmentation and ensuring a more inclusive, stable and equitable global AI ecosystem.

Future research should employ longitudinal designs to systematically track the dynamics of AI protectionism, regulatory change, and international cooperation over time, particularly amid rapid technological and institutional transformations. It is also advisable to extend the analytical framework to non-European and global contexts—including the United States, China, and countries of the Global South—to enable comparative analysis of different models of artificial intelligence governance. Further studies should differentiate between specific forms of AI protectionism, such as data regulation, export controls, standardisation policies, and industrial subsidies, and examine their distinct effects on market fragmentation, innovation capacity, and international competitiveness. In doing so, it is important to incorporate additional institutional and socio-cognitive variables, including trust in institutions, regulatory legitimacy, political preferences, and public perceptions of technology, in order to gain deeper insight into the mechanisms shaping national AI strategies. Finally, future research should focus on hybrid governance models in which protectionism and international cooperation coexist, with particular emphasis on the conditions under which international cooperation can mitigate the negative effects of fragmentation in the global AI market.

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Quantifying the Environmental Impact of AI: Analysis of Training CO_2 Emissions of Generative AI Models

Original scientific paper

Dejan Miljenović[1], Darko Ban[2]

ABSTRACT

The advancement of large-scale AI models raises considerations in regards to their energy and carbon efficiency. Increasing the density of a neural network, and the number of parameters, affects computational requirements and energy efficiency per generated token. Large AI models tend to require disproportionately large amounts of computational resources. This research focuses on generative AI models within machine learning, using regression analysis to examine how the model type, architecture, deployment scale, and utilisation patterns affect carbon intensity. This research identifies the potential increase in energy demand from the development of large generative AI models and the technological solutions that can offset the densification of neural networks. Empirical results show that dense transformer models trained on legacy hardware emit up to 2.4 tCO_2e per billion tokens, while MixtureofExperts (MoE) architectures reduce emissions to below 0.05 tCO_2e per billion tokens. Modern hardware generations reduce emissions by approximately 39%, while MoE architectures achieve reductions exceeding 50%, controlling for data centre efficiency and model type. Research results confirm that the hardware specifications and neural network architecture significantly influences the carbon efficiency of AI models, which raises concerns since major producers often rely on grids with a low share of renewable energy. Inference, due to its use after training, can over time have a greater carbon footprint than the

1 *Associate professor, University of Rijeka, Faculty of Economics and Business, Ivana Filipovića 4, 51000 Rijeka, Croatia. Scientific affiliations: corporate sustainability, environmental and social risks in business, social entrepreneurship, sustainable value management. Phone: +385 51 355 136. E-mail: dejan.miljenovic@efri.uniri.hr.*

2 *Doctoral student, University of Rijeka, Faculty of Economics and Business, Ivana Filipovića 4, 51000 Rijeka, Croatia. Scientific affiliations: energy and environmental economics, sustainable investing, sustainability reporting, corporate social responsibility, green financial instruments. Phone: +385 91 550 4797. E-mail: darko.bann@gmail.com.*

training phase. In economic models, parameters are linked to token output, and models capable of producing longer and more complex outputs generally have a higher parameter count. This underscores the need for more radical optimisation and improvements in the design of data centres and hardware. During the training phase, hardware typically operates near capacity, resulting in peak utilisation of the latest generation of deep learning accelerators. The higher nominal power requirements and subsequent electricity consumption of newer accelerators are often underestimated, while their idling during deployment leads to higher emissions. This research highlights the need for Green AI, optimised deployment, and energy-efficient model design to advance sustainable AI development.

Keywords: *AI model, Green AI, Carbon footprint, Data centre efficiency, Sustainable computing*

JEL classification: *C55, C61, C63, Q01, Q3*

1 Introduction

Energy consumption and environmental impacts associated with training models have been growing exponentially, even after the implementation of reduction strategies such as the shifting of operations to locations with less carbon-intensive electricity mixes (Morand et al., 2025). This paper aims to define the metrics and methodologies for reporting the carbon footprint of AI development and to offer recommendations on how to align these with broader sustainability goals. AI model developers seldom disclosed the carbon footprint of their AI systems, leaving researchers to make their best estimate (Maslej et al., 2024). With the reduction of AI training and inference, operational carbon footprint has emerged as a dominant area of research (Acun et al., 2023). The increasing demand for computational resources to support advanced AI models requires a comprehensive evaluation of their energy consumption and carbon emissions (Chen et al., 2022; Kneese & Young, 2024). The spread of generative AI has intensified scrutiny regarding its sustainability, leading to a need for robust evaluation methods of its environmental impact (Berthelot et al., 2024).

This research delineates a power usage method for calculating CO_2 emissions for generative AI, by applying the Stanford Method pioneered by Patterson et al. (2021). The chosen approach allows for a direct evaluation of the operational phase's environmental burden, which is critical, given the continuous power demands of large-scale AI models. This approach has focused on direct and environmental contribution of AI operations, isolating them from the complete life cycle assessment that would also take into account manufacturing and waste-disposal emissions. The Stanford Method enables evaluation of design choices in architecture and operational conditions with direct consequences for carbon emission, and in this manner providing information needed for this research. Generative AI is potential for economic development, but it is responsible for immense environmental devastation in the virtual world

(Berthelot et al., 2024). Electricity requirements of AI infrastructure, data centres, and their location energy mix are one of the primary drivers of CO2 emissions (Devarakota et al., 2025). The energy used in training deep-scale AI models represents huge operational carbon footprints, requiring more efficient algorithms and green practices (Tabbakh et al., 2024). The energy requirement of AI machine learning prompts the need for moving from non-renewable to renewable energy resources for AI machines and the creation of more energy-efficient algorithms (Mitu & Mitu, 2025; Taddeo et al., 2021). Large-scale AI models have significant energy demands, prompting the need for sustainable AI development (Singh, 2025). Development of AI models involves energy consumption, carbon emissions, water usage, transparency, and wider environmental and social implications related to these computationally intensive models (Shi et al., 2025). Global trends indicate that even though the energy consumption of AI will keep growing, technological advancement will guarantee its relative decline (de Vries, 2023; Sevilla et al., 2022). Enhanced AI technology offers clear performance and greater overall demand for computing power.

There is a lack of studies that have examined broader models, including AI model types, architecture, neural network weight, hardware, and data centre power usage effectiveness in relation to GHG emissions. Due to the lack of normalized metrics for drawing comparison between model training carbon efficiency on equal grounds over scales, e.g., per billion parameters or per token, relative sustainability estimation is hard. So far, most research has been founded on standalone case studies and not comparative cross-model studies resulting in a gap in cross-section research of AI models with different architectures and varying neural network weights (Lee et al., 2024). The analysis of energy consumption and carbon footprint of many different AI models remains unexplored (Chakraborty, 2024; Tabbakh et al., 2024). Moreover, a gap can be found in the creation of standardized and open frameworks for publishing energy consumption and emissions data by different AI model developers, thus making comparison and accountability difficult (Maslej et al., 2024). Inadequate methodologies in AI carbon footprint measurement impede the creation of industry-wide benchmarks and best practices, and obstructs advancements towards more sustainable AI development and deployment (Wynsberghe, 2021). There is a need for more detailed data on the environmental impact of specific AI model types and architectures, and their neural network configurations (Luccioni et al., 2025a).

This research provides empirical studies that systematically disentangle how different hyper-parameters, network depths, and model complexities contribute to the overall environmental footprint of AI models. By moving beyond generalized estimations, it advances the emerging paradigm of Green AI.

Hypotheses

> **H1**: Generative AI model architecture significantly influences carbon efficiency during training, while controlling for model type, parameter count, hardware type, and generation, as well as the effectiveness of data centre power usage.

H2: Hardware type and generation have a significant impact on the carbon efficiency of AI model training and the optimization of hardware can lead to substantial reductions in carbon emissions.

2 Literature review

The academic field of Green AI continues to expand as a result of researchers' effort in exploring carbon-efficient computing systems in their analyses of the environmental effects of AI models. Hardware enhancement can lower the demand for energy and enable better performance and financial gains. Tabbakh et al. (2024) show that large AI systems produce significant operational carbon emissions, and that the training of the GPT-3 model consumes 1,287 MWh of electricity, which can power more than 120 average United States homes, resulting in an estimated 500–600 tCO_2e, depending on the regional electricity mix. Verdecchia et al. (2023) and Clemm et al. (2024) state that AI researchers and developers should assume responsibility for the carbon emissions during the development and deployment of AI models, instead pf relying on sustainability features as an add-on after deployment. It is important to include sustainability in AI system design. Singh (2025) assesses multiple approaches to calculate carbon emissions through his research in order to examine algorithm energy usage with hardware specifications, and operational power consumption. The Green AI system allows users to evaluate performance levels between various AI system designs. The research on AI models continues to investigate the Jevons paradox because efficiency improvements lead users to consume more. Tabbakh et al. (2024) point out that each advance in hardware or algorithmic design tends to increase demand, effectively erasing the advantages that might have been realised. The machine learning performance improvement has created larger complex AI models which produce significant carbon emissions (Zhou et al., 2023). Pachot and Patissier (2023) explain that AI energy efficiency programs in the United States aim to reduce the expenses of AI development while, at the same time, decreasing AI energy consumption and keeping the same levels of national energy self-sufficiency. Hua et al. (2025) and BolónCanedo et al. (2024) propose that environmental costs should become an evaluation metric which would guide model development toward responsible practices. Gültekin et al. (2023) observe that environmental efficiency remains a subject of debate at major AI conferences and discover that sustainability plans do not match the actual research outputs. The speed of hardware operation affects deployment and model expansion, resulting in increased energy consumption. Data centres currently account for approximately 2–3% of global electricity consumption, with AI workloads representing a rapidly growing share (de Vries, 2023). Projections suggest that global data centre electricity demand could double by 2026, largely driven by generative AI training and inference (Wu et al., 2024).

Luccioni et al. (2025b) demonstrate that AI climate effects surpass direct impacts and that the focus on carbon emissions through tunnel vision limits insight into real effects, thus creating a need for interdisciplinary frameworks that could identify distant indirect effects and complex infrastructural dependencies. The paradoxical character of AI is that it affects economic growth, and it is a source

of ecological strain, a tension which has been foregrounded by Pimenow et al. (2024) and Silva et al. (2023), who demonstrated that AI technology improves operational efficiency in business sectors while AI development creates obstacles for achieving carbon neutrality targets. Bolte and Wynsberghe (2024) and Dubey and Alam (2024) developed entire frameworks to integrate environmental metrics into algorithms while assessing the entire social-technical framework of AI systems, and showed that AI performance improvements become worthless when rebound effects are not controlled through specific policy interventions. Sustainable AI development requires the implementation of particular modifications at design and system levels because AI computational efficiency improvements can result in higher carbon emissions (Paracolli & Arquilla, 2023; Mhlanga, 2025). Research studies on the sustainability of cloud computing can cover the entire life cycle of the system, measuring carbon emissions that occur during hardware production and infrastructure deployment, as well as water consumption. (Falk et al. 2025; Wu et al., 2024; Chakraborty, 2024; Desroches et al., 2025; Li et al. 2023; Zhao et al. 2023; Maslej et al., 2024). A holistic method is not necessary within this research as it deals with the identification of efficiency gains in the training operations of large AI models.

Bolón-Canedo et al. (2024) explain that AI technology delivers major technological advantages and economic value, but also add that the process of training large models requires large amounts of energy, which, in turn, produces substantial operational carbon emissions. The training process of complex deep learning AI models with large scale requires electricity consumption that matches the power needs of entire cities (Wright et al., 2023; Mitu & Mitu, 2025). AI development encounters a major obstacle because scientists fail to investigate environmental elements that remain understudied during research and development (Winsta, 2025). Small changes in hyper-parameters or AI dataset management lead to major variations in energy consumption. AI environmental effects result from combined factors of algorithm design, hardware choice, and data centre operational efficiency (Li et al., 2021; Clemm et al., 2024). Comparing the efficiency of GPUs and TPUs under different workloads and analysing the influence of regional energy mixes is important to understand how infrastructure choices affect carbon intensity (Tabbakh et al., 2024). The absence of sustainable practices in standard AI development workflows calls for new algorithms, which will reduce computational requirements and establish evaluation methods for AI model carbon emissions through platforms such as Code Carbon and Machine Learning CO_2 Calculator (hereafter MLCO2) that provide real-time monitoring and reporting transparency (Luccioni et al., 2023; Liu et al., 2022; Wynsberghe, 2021). The Green AI academic community promotes transparency and energy efficiency through mandatory disclosure of energy usage data and the computational complexity metrics in AI research publications. This system enables users to be decision makers and developers in choosing sustainable AI solutions through competitive market operations (Taddeo et al., 2021; Budennyy et al., 2022; Luccioni et al., 2024).

The deployment of optimised AI model architectures leads to a 90% decrease in power usage, demonstrating that AI frameworks must balance operational efficiency with sustainable practices (Mitu & Mitu, 2025; Luccioni et al.,

2025a; Wu et al., 2024; Kónya & Nematzadeh, 2023). The new methods of machine learning and edge computing enable decentralised computation, which decreases data centre energy usage, minimises data transmission, and allows organisations to use clean local power sources for applications that require privacy protection and data control. The fast-growing generative AI models generate dual effects that affect our communities both positively and negatively. Promising technological progress through efficiency and innovation exists, but it is essential to recognize the need for carbon-frugal computing methods and sustainable AI system development. The AI community must address the Jevons paradox while developing both the evaluation metrics and the transparent systems in managing its environmental effects.

3 Methodology

The research applies the Stanford Method for CO_2e estimation developed by Patterson et al. (2021) to determine the energy-related carbon footprint of AI models. The method does not include direct onsite emissions or supplychain and embodied emissions associated with hardware manufacturing and endoflife disposal. The Stanford Method abandoned the complete Green AI framework, which incorporates embodied emissions. While embodied emissions are critical in a complete lifecycle assessment, they are not the primary focus here, as the research aims to establish relationships between specific independent variables (model parameters, Power Usage Effectiveness, hardware, model type, and architecture) and the dependent variable, CO_2e emissions. The Stanford Method is primarily based on the energy consumption during model training and inference, and uses the MLCO2 tool to calculate total computational operations, which are converted into energy usage before the system calculates CO_2e emissions based on electricity carbon intensity values (Wu et al., 2021).

Carbon emissions are calculated using the $MLCO_2$ equation as follows:

$$CO_{2e} = N \times P \times T \times PUE \times CI \quad (1)$$

This equation estimates the operational CO_2e emissions generated during the training of an AI model, and the notation is defined as follows:

- N - number of computational accelerators (GPUs or TPUs).
- P - average electrical power draw of a single accelerator, expressed in kilowatts (kW).
- T - total training duration, measured in hours.
- PUE - Power Usage Effectiveness of the data centre, accounting for additional electricity consumption related to cooling, power delivery, and supporting infrastructure.
- CI represents the carbon intensity of electricity (kg CO_2e per kWh) corresponding to the geographical location of the data centre.

There is an alternative approach to estimate CO_2e, known as the Chinchilla Method, introduced by Hoffmann et al. (2022), which relies on scaling laws and describes how language model parameters grow with training token volume and data set size. The Chinchilla Method uses floating-point operations per second recorded during model training and execution to measure scaling performance while providing methods to optimise performance from restricted computational resources.

The Stanford Method is used to calculate the CO_2e emissions for 62 generative AI models with a standardised approach in the entire dataset. The calculated CO_2e values will serve as the dependent variable in a multiple linear regression model. Impact of the independent variables Power Usage Effectiveness of training data centres, hardware generations, model types, and architectural details on carbon emissions will be analysed. This research will perform an extensive evaluation to determine which elements affect carbon emission output. AI development needs precise carbon evaluation of different model structures and training approaches to enable technological progress with lower environmental impact (Patterson et al., 2021; Hoffmann et al., 2022). There are concerns about the reporting standards and presentation of data on the environmental impacts of large AI models. The estimation of carbon footprints for large language models should go beyond carbon footprint estimation based on GPU usage during training, including indirect emissions in the calculation (Faiz et al., 2023). The Green AI research field continues to expand, and additional data is needed to determine which AI model components produce the highest carbon emissions (Dauner & Socher, 2025). The exact effects of different neural network weight values, their energy efficiency optimisation methods, and carbon emissions have not been fully studied (Liu & Yin, 2024). The lack of standardised methods for the disclosure of AI system carbon emissions makes it impossible to conduct proper analysis and to develop suitable reduction strategies. (Dubey & Alam, 2024; Liu & Yin, 2024). AI developers can make sustainable decisions regarding the implementation of AI models through the assessment of carbon emissions, and these decisions are more effective when the development stages with the with the highest emissions are recognised.

The Stanford and Chinchilla methods face criticism because they restrict their analysis to AI direct carbon emissions while ignoring all other value chain emissions. This research aims to determine the impact of AI model configurations on CO_2e, and a holistic approach is not applicable; however, it is important to note that such an approach has been discussed and has its advocates. Faiz et al. (2023) claim that current tools, including $MLCO_2$, rely on GPU usage, and fail to provide accurate carbon footprint calculations for new neural networks because they cannot handle different model types. The evaluation of AI models' carbon footprint requires new methods that provide better standards to assess environmental impacts beyond power usage (Taddeo et al, 2021; Luccioni et al., 2023). The development of AI systems requires researchers to expand the existing system estimation tools and to create new algorithms that handle the unpredictable nature of carbon emissions and to move past training phase limitations (Hacker, 2023; Jagannadharao et al., 2023). The current research lacks empirical data, which prevents the development of new energy-efficient algorithms and hardware

systems (Gowda et al., 2025). The critics' expectations may be overly ambitious, as there is a lack of sufficient data to carry out such comprehensive studies. Greater transparency from corporations developing AI technologies is also needed. Alder et al. (2024) show that current regulatory systems remain superficial because they do not establish clear guidelines for AI inference power consumption and AI system carbon emissions in climate disclosure reports. The growing energy demand of AI development and its environmental footprint are not adequately addressed in existing disclosure and reporting standards.

4 Empirical data and analysis

This research systematically compiled a dataset from available research papers, technical reports, and official releases from organisations developing generative AI models. Modeled on Patterson et al. (2021) and Kaack et al. (2022), the dataset for each model includes architectural specifications, parameter count, training data volume measured in tokens, hardware type and power rating, training duration in graphics processing unit (hereafter GPU) hours, and reported or estimated CO_2 emissions. The research method used primary sources to preserve the authentic methods of model development, while secondary methods verified the environmental impact assessment results. The Stanford MLCO2 tool was used to calculate carbon emissions through analysis of hardware details, data centre power usage effectiveness (PUE), training duration, and location-based carbon intensity factors when direct measurement data are not available. The method provided uniform results for all architecture types, which included encoder-only, decoder-only, encoder-decoder transformers, and Mixture-of-Experts (MoE) models. The study selection and appraisal process followed a systematic data collection method to achieve transparency and reproducibility. Each reported or calculated environmental metric was cross-validated against multiple sources when available. There is no single database that provides an overview of the technical specifications of a large number of AI models.

The study documented all methodological assumptions, which included GPU cluster extrapolations and fine-tuning run results to handle different CO_2 calculation methods. The research design enables conducting a full evaluation of environmental effects between different generative AI models from the complete training process. The research shows how model complexity influences computational needs and sustainability results. The system is more accurate when primary data is used together with $MLCO_2$ carbon emission estimation to measure the carbon effects of AI model training and fine-tuning operations (Sánchez-Mompó et al., 2025; Singh, 2025). The comparison between models became possible through token-based CO_2 emission normalisation. Carbon emissions per token serve as standardised metrics that enable the calculation of AI model carbon emission effects (Wilhelm et al., 2025). The Stanford Method is better suited for the normalization of carbon emissions per token than the Chinchilla Method, which uses the number of tokens as a factor in the calculation of carbon emissions.

4.1 Generative AI model training data

The dataset presents 62 AI models launched between 2018 and 2025 coming from leading research groups and tech giants, such as Google, OpenAI, Meta AI, DeepMind, Microsoft, EleutherAI and others. The model entries contain complete metadata that show technical details, model structure, training data size, hardware details, and training carbon emission for easy evaluation of their energy consumption and carbon impact. The research data originated from peer-reviewed articles, open-access repositories and official reports from organizations that created the models. The following table presents the primary dataset that serves as the basis for analysis.

Table 1: AI model data

No	AI model	Model type	Parame-ters (B)	Training tokens (B)	Data centre PUE	Hardware	Architecture	CO_2e t per token (B)
1.	BERT	LLM (NLP)	0.34	2	1.10	TPU v3	Encoder-only	0.49
2.	BLOOM	LLM	176.00	366	1.20	A100	Decoder-only	0.63
3.	Chinchilla	LLM	70.00	1400	1.20	V100	Decoder-only	0.06
4.	Codex	Coding LLM	12.00	100	1.10	A100	Decoder-only	0.27
5.	CTRL	LLM	1.63	5	1.20	V100	Decoder-only	0.54
6.	DialoGPT-0.117B	Dialogue Model	0.12	1	1.18	V100	Decoder-only	2.40
7.	DialoGPT-0.345B	Dialogue Model	0.35	2	1.18	V100	Decoder-only	0.75
8.	DialoGPT-0.762B	Dialogue Model	0.76	4	1.18	V100	Decoder-only	0.55
9.	ERNIE1.0	LLM	0.11	10	1.30	V100	Encoder-only	0.47
10.	ERNIE2.0	LLM	0.34	15	1.30	V100	Encoder-only	0.41
11.	Galactica	Multimodal LLM	120.00	50	1.20	A100	Decoder-only	0.29
12.	Glyce	NLP	0.34	2	1.30	V100	CNN-augmented	0.80
13.	GPT1	LLM	0.12	1	1.10	V100	Decoder-only	0.50
14.	GPT2	LLM	1.50	10	1.10	V100	Decoder-only	0.33
15.	GPT3	LLM	174.60	300	1.10	V100 Cluster	Decoder-only	1.84
16.	GPT-J	LLM	6.00	50	1.10	A100	Decoder-only	0.27
17.	GPT-Neo 1.3B	LLM	1.30	20	1.10	A100	Decoder-only	0.14

No	AI model	Model type	Parame-ters (B)	Training tokens (B)	Data centre PUE	Hardware	Architecture	CO_2e t per token (B)
18.	GPT-Neo 2.7B	LLM	2.70	20	1.10	A100	Decoder-only	0.27
19.	GPT-NeoX	LLM	20.00	40	1.10	A100	Decoder-only	0.27
20.	InstructGPT	LLM	175.00	100	1.10	A100	Decoder-only	0.26
21.	LaMDA	Dialogue LLM	137.00	50	1.10	TPU v3	Decoder-only	1.40
22.	MegatronGPT2	LLM	0.35	10	1.18	V100	Decoder-only	0.28
23.	MT-DNN	LLM	0.33	5	1.18	V100	Encoder-only	0.28
24.	OPT	LLM	175.00	500	1.20	A100	Decoder-only	0.15
25.	PaLm	LLM	540.00	1200	1.10	TPU v4	Decoder-only MoE	0.10
26.	RoBERTa-1	LLM	0.13	10	1.20	V100	Encoder-only	0.43
27.	RoBERTa-2	LLM	0.36	15	1.20	V100	Encoder-only	0.39
28.	T5	LLM	11.00	10	1.10	TPU v3	Encoder-decoder	0.42
29.	T5-0.78B	LLM	0.78	2	1.10	TPU v3	Encoder-decoder	1.40
30.	T5v1.1	LLM	11.00	5	1.10	TPU v3	Encoder-decoder	0.84
31.	UL2	LLM	20.00	400	1.10	TPU v4	Decoder-only MoE	0.08
32.	XLM	Multilingual LLM	0.34	5	1.20	V100	Encoder-decoder	0.58
33.	XLNET	LLM	0.34	5	1.10	TPU v3	Autoregressive transformer	1.40
34.	Meena	Dialogue LLM	2.60	20	1.12	TPU v3	Evolved Transformer	1.40
35.	BlenderBot2	Dialogue LLM	3.00	20	1.20	A100	Seq2Seq Transformer	0.60
36.	BlenderBot3	Dialogue LLM	175.00	50	1.20	A100	Decoder-only (OPT-175B FT)	0.38
37.	WebGPT	Dialogue / QA LLM	175.00	10	1.10	V100	Decoder-only (GPT-3 FT)	0.26
38.	Sparrow	Dialogue LLM	70.00	10	1.20	TPU v3	Decoder-only (Gopher 70B FT)	0.25
39.	Vicuna	Dialogue LLM	13.00	20	1.20	A100	Decoder-only (LLaMA FT)	0.60
40.	Koala	Dialogue LLM	13.00	20	1.20	A100	Decoder-only (LLaMA FT)	0.36
41.	Alpaca	Dialogue LLM	13.00	20	1.20	A100	Decoder-only (LLaMA FT)	0.24

No	AI model	Model type	Parame-ters (B)	Training tokens (B)	Data centre PUE	Hardware	Architecture	CO_2e t per token (B)
42.	ChatGLM	Dialogue LLM	6.20	20	1.10	A100	GLM Decoder	0.31
43.	Grok-1	LLM	314.00	500	1.10	H100/A100	Dense MoE	0.08
44.	Jukebox-1B	Music generation	1.00	50	1.10	512 V100 GPUs	Decoder-only	0.19
45.	Jukebox-5B	Music generation	5.00	10	1.10	1536 V100 GPUs	Decoder-only	0.24
46.	Cerebras-GPT 1.0	LLM	0.11	2.22	1.20	Cerebras CS-1 WSE	Decoder-only	0.20
47.	Cerebras-GPT 2.0	LLM	0.26	5.12	1.20	Cerebras CS-1 WSE	Decoder-only	0.20
48.	Cerebras-GPT 3.0	LLM	0.59	11.8	1.20	Cerebras CS-1 WSE	Decoder-only	0.20
49.	Cerebras-GPT 4.0	LLM	1.30	26	1.20	Cerebras CS-2 WSE	Decoder-only	0.14
50.	Cerebras-GPT 5.0	LLM	2.70	54	1.20	Cerebras CS-2 WSE	Decoder-only	0.13
51.	Cerebras-GPT 6.0	LLM	6.70	134	1.20	Cerebras CS-2 WSE	Decoder-only	0.14
52.	Cerebras-GPT 7.0	LLM	13.00	260	1.20	Cerebras CS-2 WSE	Decoder-only	0.14
53.	GShard	LLM	600.00	204	1.10	TPU v3 (2048)	MoE encoder-decoder	0.02
54.	Switch Transf.	LLM	1600.00	300	1.10	TPU v3	MoE decoder-only	0.03
55.	GLaM	LLM	1200.00	1600	1.10	TPU v4	MoE decoder-only	0.00
56.	Wu Dao 2.0	LLM	1750.00	1750	1.10	HPC cluster (BAAI)	Multimodal MoE	0.01
57.	DeepSeekMoE	LLM	600.00	1480	1.20	GPU cluster	MoE decoder-only	0.07
58.	Mixtral 8×7B	LLM	56.00	1000	1.20	GPU cl (A100/ H100)	MoE decoder-only	0.01
59.	FLAN-MOE	LLM	1200.00	280	1.10	TPU v4	MoE decoder-only. tuned	0.01
60.	OpenMoE	LLM	1200.00	280	1.10	TPU v3/v4	MoE (decoder-only)	0.01
61.	Lory	LLM	1200.00	280	1.10	GPU cluster	MoE decoder-only	0.01
62.	MoEfication OPT MoE	LLM	1200.00	280	1.10	GPU cluster (Meta)	MoE decoder-only	0.01

Source: Authors

Carbon emissions were calculated using the Stanford Method and normalized per billion tokens to ensure comparability across different model sizes and training setups. Power Usage Effectiveness (PUE) and CO_2 emission factors

were applied according to published energy-efficiency metrics for respective data centres. There is substantial variation in carbon emissions, where Mixture-of-Experts (MoE) based architectures achieve notably lower CO_2 per token compared to dense GPU-based systems. In this research, variable parameters (hereafter PARAM), power usage effectiveness (hereafter PUE), model type (hereafter MT), hardware (hereafter HARD), and architecture (hereafter ARCH) are independent variables. Variable carbon emission per token (hereafter CE) is the dependent variable.

4.2 Multiple linear regression model

Multiple linear regression (MLR) is used to model the relationship between the dependent variable and multiple independent variables, assuming predictor independence (Upendra et al., 2023). The high correlation between independent variables in Ordinary Least Squares regression can produce unreliable estimates and increase values of standard errors (Hoque et al. 2025; Baird & Bieber, 2023). The identification of multicollinearity remains essential because elimination of variables with high correlation produces more accurate parameter values (Farrar & Glauber, 1967; Rumere et al., 2021). The failure to handle multicollinearity produces wrong interpretations of predictor effects and reduces statistical power (Alin, 2010). The stability of MLR becomes unstable when the data shows homoscedasticity violations together with non-normal residual distributions and non-linear relationships (Marisetty, 2025; Adhikari, 2022). The analysis of multicollinearity between independent variables was conducted using variance inflation factors (hereafter VIF) and correlation analysis before fitting the MLR model. The analysis used VIF values above 5 to identify problematic multicollinearity, which required variable elimination (Iftikhar et al., 2024; Abedi, 2024).

To enable inclusion of categorical variables, binary coding was applied as follows:

- MT was coded as 1 = Dialogue model, 0 = Other models.
- HARD was coded as 1 = New generation hardware (e.g., A100, GPU, TPUv4, CS2-WSE), 0 = Other hardware types (e.g., V100, TPUv3, CS1-WSE).
- ARCH was coded as 1 = Mixture-of-Experts (MoE), 0 = Other architectures (e.g., encoder-only, decoder-only, encoder–decoder).

Model assumptions, normality and homoscedasticity of residuals, were evaluated through Q–Q plots and Breusch–Pagan tests. Variable CE observations exhibited moderate right skew, and it was considered to use log-transformed dependent variable. The Q–Q plot for the log-transformed CE data shows points that follow the line, which indicates that the data follow a normal distribution. After evaluation, the raw CE values were selected as the dependent variable for the regression analysis to maintain interpretability in the original emission units. The Breusch–Pagan test for homoscedasticity shows no evidence to reject H_0 for predictors PUE, HARD, MT, and ARCH, and confirms that residuals maintain constant variance. The variable

PARAM shows heteroscedasticity because its extensive range indicates that residual variance depends on its observed values, which produces a statistically significant coefficient in the Breusch-Pagan auxiliary regression. This is consistent with the expectation that extreme values in PARAM cause non-constant residual variance. The following table shows the MLR model correlation matrix.

Table 2: Correlation matrix

	PARAM	PUE	HARD	MT	ARCH	CE
PARAM	1.00					
PUE	-0.36	1.00				
HARD	0.29	-0.12	1.00			
MT	-0.20	0.11	-0.02	1.00		
ARCH	0.81	-0.34	0.37	-0.27	1.00	
CE	-0.34	0.01	-0.44	0.35	-0.42	1.00

Source: Authors

The correlation matrix results show relations between tested model variables. Analysis of multicollinearity is performed to determine if the variables influence each other. The variable PARAM has a positive correlation with ARCH, which indicates strong multicollinearity between these two predictors. The variable PARAM was initially included in the MLR model, but high multicollinearity with ARCH and heteroscedasticity led to its exclusion from the final model. The heteroskedastic variable PARAM would be log-transformed and retained in the model, but due to multicollinearity, it has been excluded from the model to prevent redundancy and instability in regression estimates. The following table shows output VIF values of the MLR model.

Table 3: Variance inflation factors

Variable	VIF	VIF without PARAM
PARAM	12.30	/
PUE	1.30	1.09
HARD	2.10	1.67
MT	1.80	1.80
ARCH	5.60	1.59

Source: Authors

The high VIF for PARAM confirms severe multicollinearity with ARCH. The remaining variables have acceptable levels of multicollinearity. The results of the correlation matrix and the VIF test are consistent, which excludes PARAM from the MLR model. The results of the VIF test without PARAM indicate a

better model fit without the specified variable. Based on the pretesting results, the final specification of the MLR model is ready. The method improved the data explanation capabilities of the model while minimising errors that occurred during parameter estimation.

4.2.1 Multiple linear regression model equation

A multiple linear regression (MLR) model is employed to estimate the relationship between AI model characteristics and carbon emissions during training. The dependent variable is CE, and the independent variables include PUE, HARD, MT, and ARCH.

The final MLR model is as follows:

$$CE=\beta_0+\beta_1 PUE+\beta_2 HARD+\beta_3 MT+\beta_4 ARCH+\epsilon \quad (2)$$

The assumptions of normality and homoscedasticity were re-evaluated for the final model. The Q-Q plot for the residuals of the reduced model showed points closely aligned, indicating approximate normality, which is consistent with the findings for the log-transformed CE variable. To address the moderate right skew in CE, a log-transformed version of the dependent variable was evaluated. However, the AIC comparisons and Q-Q plot for the residuals favoured retaining the untransformed CE for interpretability in its original units of carbon emissions. The Breusch-Pagan test for the reduced model showed that the data is homoscedastic because the p-value exceeded 0.05, which indicated that the exclusion of the PARAM fixed the heteroscedasticity problem. Before laying out the linear regression (MLR) results for the data set containing the variables PUE, MT, ARCH, and CE, a series of diagnostic checks and modelselection steps were carried out to make sure the final model is robust and valid.

The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were employed to evaluate the reduced model. The model with PUE, HARD, MT, and ARCH variables produced lower AIC and BIC values than the combined model which also included PARAM. The model achieved better parsimony through PARAM exclusion because it maintained its ability to explain the data. The research evaluated the potential synergy effects of HARD and ARCH systems to determine how modern hardware systems with Mixture-of-Experts architectures affect CE when used together and confirmed synergy. The AIC analysis showed that the simpler model provided a better fit than the combined model, which supports its continued use.

The Shapiro-Wilk test indicated that residuals followed an approximate normal distribution, confirming that the model met all MLR assumptions. The residual plots showed no patterns when compared to fitted values. This also stands for each predictor variable, confirming the requirements for linear relationships and constant variance. The Cook's distance analysis showed which observations had the most impact, but the model coefficients stayed consistent when extreme values appeared in the CE variable. Robust standard errors using

the Heteroscedasticity-Consistent 3 method (hereafter HC3) were applied to ensure reliable inference, addressing any residual heteroscedasticity not detected for PUE, HARD, MT, and ARCH in the Breusch-Pagan test.

4.2.2 Model estimation methodology and expected carbon footprint

The MLR model used the HC3 standard errors method to make robust estimates because it addresses non-constant residual variance in CE across observed AI models. The HC3 method developed by MacKinnon and White (1985) handles heteroscedasticity by modifying standard error calculations to make accurate t-statistics and p-values for the predictors PUE, HARD, MT, and ARCH. The method enables better analysis of the AI training environment while generating more precise regression results. The MLR model was estimated in EViews software using the command equation eq1.ls(cov=hac,white,hc3) ce c pue hard mt arch that instructs EViews to use HC3.

We then used Ordinary Least Squares (OLS) estimation with HC3 standard errors for model estimation and performed all necessary diagnostic tests. The expected CE values for BERT, Mixtral 8×7B, and Vicuna AI models were calculated to evaluate their environmental effects. This was done based on the comparison with actual measurement results. The research uses BERT, Mixtral 8×7B, and Vicuna generative AI models because they offer diverse prediction capabilities and represent three different model types: BERT as an encoder-only model, Mixtral 8×7B as a MoE model, and Vicuna as a dialogue model. The MLR HC3 equation generates expected CE values by applying predictor values (Table 1) to produce results that can be compared to observed CE values. The calculated results are presented in the following table.

Table 4: Expected carbon emission values

Model	PUE	HARD	MT	ARCH	Expected CE (t/B tokens)	Observed CE (t/B tokens)
BERT	1.10	0	0	0	0.50	0.49
Mixtral 8×7B	1.20	1	0	1	0.03	0.01
Vicuna	1.20	1	1	0	0.85	0.60

Source: Authors

Results in Table 4 show an insignificant difference between expected and observed CE values for BERT and Mixtral models. The HC3 MLR model went well on this stratified random test, but Vicuna's slightly higher predictions needs further investigation to explain the regression results. The higher discrepancy on Vicuna is likely due to word piece-level dialogue alignment which requires more finetuning due to the heavier computation per token cost than the base model pretraining. The training tuning, which includes learning from human feedback and conversational context management, brings workload features that are not completely reflected by architecture and hardware binary clues.

The HC3-based estimation methodology allows for complete evaluation of environmental impact of generative AI by means of the MLR model analysis.

5 Results and discussion

The MLR model enables the quantification of linear relationships between independent and dependent variables, providing regression coefficients, measures of fit (R^2), and statistical significance of predictors. The model was estimated using the HC3 covariance estimator to obtain robust standard errors, generate proper t-statistics and p-values to address heteroscedasticity in the residuals, and precisely assess the effects of both continuous and categorical predictors on CE. The results show estimated coefficients with their corresponding adjusted standard errors and complete model performance evaluation metrics. The analysis provides complete data relationships while following model restrictions and needing further validation procedures. The model included binary categorical variables to represent model type, hardware generation, and architecture, because these variables are categorical and explain structural variations in AI workloads.

5.1 Results and analysis

The MLR HC3 model estimates are presented in Table 5 with their corresponding standard errors, t-statistics, and significance levels. The table presents a summary of how categorical and continuous variables affect CE to enable an analysis of the proposed relationships. In this research, the focus of the analysis is on hypotheses H1 and H2, which assume the influence of hardware generation and neural network architecture on CE.

Table 5: MLR HC3 regression output

Dependent Variable: CE
R-squared: 0.57
Adjusted R-squared: 0.55
S. Error of regression: 0.32
Sum squared resid: 5.73
F-statistics: 19.53
Prob. (F-statistic): 0.00
Akaike info criterion: -0.22
Schwarz criterion: -0.01
Durbin-Watson: 1.82
Observations: 62

Variable	Coefficient	Std. Error	t-Statistic	P-value
C	0.97	0.33	2.94	0.00
PUE	-0.42	0.27	-1.58	0.12
HARD	-0.39	0.08	-4.75	0.00
MT	0.77	0.13	5.95	0.00
ARCH	-0.54	0.10	-5.17	0.00

Source: Authors

According to the results, the model explains more than half of the variance in CE and strongly explains the data. The F-statistic confirms that the model is significant, and that the coefficients can be analysed.

It can be determined that hardware generation (HARD) is a strong predictor that affects energy efficiency. The negative coefficient β2 shows that modern hardware models (A100 GPUs, TPUv4, CS2-WSE) decrease carbon emissions by 39% when compared to using outdated hardware models, which confirms H2. New hardware technology delivers improved performance through its enhanced operational speed, reduced power usage, and heat control systems. This suggests that investment in next-generation infrastructure is needed to reduce AI's environmental footprint.

There is an indication that AI model architecture (ARCH) has a strong impact on carbon emissions. The negative coefficient β4 shows that MoE architecture implementation leads to an over 50% reduction in emission in comparison to standard encoder-only, decoder-only, and encoder–decoder models, which confirms H1. It was expected that MoE models would show lower energy consumption and emissions because they activate only certain parameters during each operation, which is confirmed by research results. AI system sustainability depends on architectural decisions and on hardware performance improvements. The model type (MT) coefficient β3 shows a positive and statistically significant connection to carbon emissions. The complex structure of dialogue models requires large training datasets, resulting in 77% higher emissions than other model types. The influence of model type on emissions needs to be investigated further by including MoE architecture dialogue models in the sample, which would have been conducted within this research if there had the possibility to collect the required data.

This analysis shows that Power Usage Effectiveness (PUE) has a negative and insignificant coefficient β1. Equipment and network structure affect emissions more than PUE. It can be determined that the data centre location and energy sources influence carbon emissions more than the differences in effectiveness.

The research results show that the implementation of MoE and other efficient architecture designs results in major reductions of carbon emissions. The research findings present various strategies to decrease AI environmental impact through efficient AI system development with advanced computer hardware deployment and neural network design based on emission

restrictions. The achievement of performance sustainability targets for large-scale and dialogue-heavy models requires hardware and architectural enhancements.

5.2 Output interpretation and discussion

The Mixture of Experts (MoE) sparse architecture, along with other sparse architectures, operates as an efficient AI design solution that supports Green AI projects. Sparse architecture functions through a different mechanism than dense architecture (e.g., traditional encoder-only or decoder-only models) because it enables selective activation of parameters. The MoE architecture has multiple subnetworks, which function as experts specialised in specific tasks or input type where a gateway mechanism directs input information to the optimal expert or a subset of experts. The dialogue task requires experts to process context information independently from response creation because their unutilized parameters stay inactive. The system activates specific parts of the model, which decreases operational requirements and results in reduced power usage and environmental impact in comparison to running the entire model. The research shows that MoE architectures outperform standard dense models in emission reduction while maintaining the efficiency standards of Green AI.

The current chip technology and cluster specifics of hardware produce lower carbon emissions than previous versions. The design of chips, which includes advanced GPUs and TPUs, and specialised AI processors, works towards achieving maximum operational performance. The modern processors use smaller manufacturing techniques, improved computational cores, and power management systems to decrease their energy consumption when performing AI operations. The current generation of processors operates at high speeds while using reduced power consumption compared to their predecessors. Improved cooling systems help decrease the power needed for temperature management.

The research shows that new hardware systems reduce environmental emissions, implying that data centres need modern equipment to support Green AI deployment. New hardware generation allows faster operations while using less power and better cluster management. The MoE architecture with sparse systems allows better AI scaling because it uses a lower number of active parameters. The environmental impact assessments of dialogue models stem from their complex computational needs, encouraging developers to implement a sparse architecture and use new hardware generation to achieve environmental sustainability. The system operates through its fundamental elements, which consist of contemporary microchips and cluster technologies. The combination of MoE designs with advanced chips and clusters enables AI development to achieve substantial reduction in emissions. The research findings require developers to create new AI models, build hardware systems, and establish strategic data centre plans for sustainable AI development.

6 Conclusions

The development of generative AI models has become a defining feature of our time, significantly influencing both the economy and society. The demand for AI models is elastic, and it is important to note that many users use the available free versions of AI models. The Jevons paradox occurs because the economy of scale reduces costs, enabling the technology to be widely used. Research and development of artificial intelligence has already yielded results, but further research should also take into account the indirect costs of AI. Considering the expected increase in energy consumption of AI data centres, it is important to provide answers to questions about the availability of electricity, the possible increase in the price of electricity, the impact of electricity consumption on the environment and the opportunity costs of AI development. If a holistic analysis of the impact of AI on the environment is carried out, then it is also necessary to consider the opposite effects where AI achieves energy savings by improving business processes. Visionaries and advocates of sustainable development, who often face short-sighted criticism, warn of a climate and energy crisis eventually caused by changes in consumer preferences, lifestyle, and technological processes. The exponential growth of generative AI models puts Green AI in the spotlight, and, thus, the regulatory frameworks for reporting data on the environmental effects of AI are expected to strengthen. In this research, the data was collected from many publications and scientific articles on AI model training, in which technical specifications and solutions are available, as well as scalability and hours of training. AI model training data is not available for some large language models such as GPT-4, which is not a good practice since it makes it difficult to estimate the energy consumption and environmental effects. Therefore, it is necessary that the development of each model is accompanied by a published research paper which would include all the standard data necessary for the calculation of environmental effects. Through the synthesis of previous research, it was determined that the data for calculating the effect of operational work on emissions is not sufficient for a clear comparison of the sustainability of different models and a holistic analysis of the life cycles of AI models.

In this research, the authors used the available AI model training data, and concluded that AI technology can be more efficient in its operations and can reduce carbon emissions. The answer lies in the efficient management of the neural network, which requires a sparse architecture and the use of new, faster chips. Progress will eventually occur, but the question is at what cost. In the move towards sustainable AI, quantum computers are becoming increasingly prominent, yet realization of their application will depend on their profitability. On the same horizon lie renewable energy sources, which confirms the accuracy of anticipating the need for clean energy.

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The Hidden Costs of Artificial Intelligence: Energy, Economic and Environmental Aspects

Original scientific paper

Andrea Arbula Blecich[1], Paolo Blecich[2], Ana Babić[3]

ABSTRACT

Users perceive large language models (LLMs) such as ChatGPT, Claude, and Gemini as digital innovations. However, the operation of LLMs incur increasing economic costs. Every user query is met by energy-intensive computations in data centres, generating costs related to electricity consumption, cooling, water consumption, and system maintenance. Electricity is the largest running cost of data centres. ChatGPT alone is accessed 2.5 billion times daily, and each query needs an average energy use of 20 Wh. Data centres hosting ChatGPT are estimated to consume electricity quantities comparable to the output of two large nuclear power plants. Global electricity consumption in data centres will rise to 945 TWh by 2030, equivalent to 3% of the total global electricity consumption by 2030. Annual global investment in data centres increased from USD 100 billion in 2015 to USD 500 billion in 2024, reflecting the need for reliable hardware. Cumulative investment will surpass USD 4 trillion by 2030, suggesting that AI development will go hand in hand with high investment, operation and maintenance costs. Environmental and resource-related costs add another layer of economic pressure. CO_2 emissions from electricity used by data centres reached 170 million tonnes in 2024 and will increase to 310 million tonnes by 2030. With the present carbon prices, €80–€100 per tonne in the EU and $20–$95 per tonne in the USA, the emissions of data centres will translate into annual carbon costs on the order of USD 10-30 billion by 2030. In addition, data centres will require 2% of global copper and silicon supply and up to 11% of gallium supply by 2030, exposing AI services to volatile

1 *Associate Professor, University of Rijeka, Faculty of Economics and Business, Ul. Ivana Filipovića 4, 51000 Rijeka, Croatia. Phone: +385 51 355 141. E-mail: andrea.arbula.blecich@efri.uniri.hr*

2 *Associate Professor, University of Rijeka, Faculty of Engineering, Vukovarska 58, 51000 Rijeka, Croatia. Phone: +385 51 651 543. E-mail: paolo.blecich@riteh.uniri.hr*

3 *Assistant Professor, University of Rijeka, Faculty of Economics and Business, Ul. Ivana Filipovića 4, 51000 Rijeka, Croatia. Phone: +385 51 355 152. E-mail: ana.babic@efri.uniri.hr*

prices of critical mineral. Overall, the economics of large-scale AI will depend increasingly on cost containment rather than solely on performance gains.

Keywords: *Artificial intelligence, Data centre costs, Electricity demand, Capital intensity, Critical minerals*

JEL classification: *O33; Q43; Q52; L86; E22*

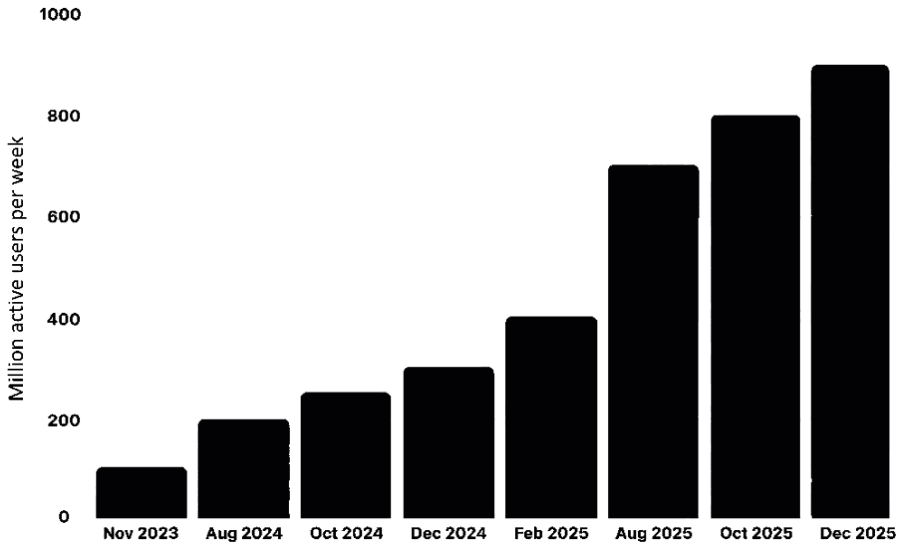
1 Introduction

For most users, Artificial Intelligence (AI) exists as an interface: a text box, an image generator, a program query. Users do not see machines or moving parts, nor the energy, material and costs necessary for running AI. The interaction between users and AI appears instantaneous and non-physical. This reinforces the idea that AI lives in the cloud, a metaphor that obscures hardware, geography, resource use. In the public sphere, AI is described in terms of models, parameters, training, and capabilities, not transformers, substations, water consumption, or energy supply.

However, the computing behind modern AI is produced by physical entities: specialized chips produced from critical minerals, racks, cooling systems with water consumption, substations, transmission lines, power plants. This article is grounded in the premise that AI constitutes a physical economy, not merely an abstract digital service.

Two observations motivate this analysis. First, global data centres consumed 415 TWh of electricity in 2024, or 1.5% of the world electricity consumption. Second, global investment in data centres had doubled since 2022 and reached USD 500 billion in 2024 (IEa, 2025). These two facts are in direct contrast against the popular claim that AI is a non-physical entity. Electricity demand is localized: power grid transport capacity, transformer availability and permitting determine whether new data centres can be connected on time. Capital expenditure is globally binding: faster servers are more expensive and limited by supply chains. Soon, these servers will be replaced by even faster ones. Server manufacture is impossible without a reliable supply of critical materials: copper for electrical distribution, silicon and gallium for semiconductors, rare-earth magnets for motors and cooling (IEA, 2025). This physical expansion closely tracks the rapid growth in AI usage. In 2023, generative AI tools were still in an early mass-adoption phase, with ChatGPT alone reaching on the order of 100 million users shortly after launch. By 2025, estimates suggest that hundreds of millions to over one billion people worldwide actively use AI systems, with ChatGPT reporting 900 million weekly active users (Fairhurst, 2025). Figure 1 shows the growth in weekly active users for ChatGPT.

Figure 1: Number of active users of ChatGPT per week



Source: Backlinko Team, 2025

Annual global investment in data centres has increased over the last decade, from USD 100 billion in 2015 to USD 500 billion by 2025. This growth is a result from the transformation of traditional data centres to AI data centres with more computational power, more space and more energy input that increase specific costs per unit of power and per unit of floor area. Capital investments by 2030 are projected to be between USD 4-8 trillion, according to different scenarios of AI investment (Noffsinger et al., 2025).

Several factors explain why total capital investments are growing this fast. AI increasing workloads are pushing rack power densities to grow, which necessitates upgrades across the entire system: faster and more capable GPUs and accelerators, ultra-fast networking, high-voltage electrical distribution, increasing UPS capacity, larger backup power generators, and advanced (liquid) cooling systems. At the same time, power availability is becoming a limitation, as data centres needs more affordable and reliable distribution grids and on-site power plants, especially from low-carbon sources such as wind, solar PV and nuclear energy.

Global capital investments are concentrated among a small set of market players, also known as hyperscalers: Microsoft (Azure), Alphabet Inc. (Google Cloud), Meta Platforms, Apple Inc. and Oracle Corporation. Slower or faster AI expansion plans of these market players can alter the annual capital investment in AI by hundreds of billions. The central question of this article revolves around the cost of AI, including energy, water and material resources needed to manufacture and run AI data centres.

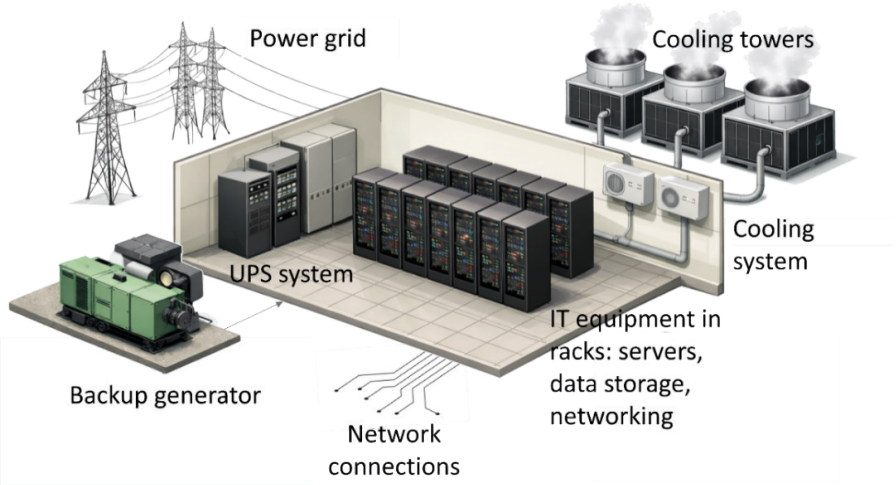
2 Energy needs of AI

Figure 2 illustrates the layout of a data centre, including the main components and their relation with each other. The key elements are as follows:

1. The power grid is the primary source of electrical power supplying the data centre under normal operating conditions.
2. UPS (Uninterruptible Power Supply) system: located inside the facility near the IT space. The UPS provides instantaneous backup power in case of grid disturbances or shortages. UPS supplies power and ensures stable operation of IT equipment and critical infrastructure during the start-up window of the backup generator.
3. Backup generator: acts as the secondary power source, supplying electricity during prolonged grid failures. Backup generators require a start-up time (10-30 seconds),
4. IT Equipment (servers, storage, networking): depicted as rows of server racks inside the data hall. This is the core function of data centres, hosting computational, data storage, and networking resources.
5. Cooling System: simplified with AC units mounted on the wall. The cooling system removes waste heat generated by the IT equipment and transfers it to the external cooling towers. Depending on heat fluxes to be removed, the cooling system can be circulated air-cooling, single-phase liquid cooling, liquid immersion cooling in dielectric liquid, two-phase cooling using a liquid boiling at low temperatures,
6. Cooling towers: located outside the building with visible evaporation losses, reject thermal energy into the atmosphere.

Overall, power flows from the power grid to the IT equipment, with the UPS and backup generators ready to kick-in in case of power grid failure. Waste heat flows from servers to the cooling system and eventually are discharged into the atmosphere by the cooling towers (Blecich et al., 2018).

Figure 2: The main components of a data centre



Source: Authors

AI is energy intensive. Data centres used 1.5% of the global electricity in 2024. Although AI is only one of several data-centre workloads, expectations of rapid growth in AI services are driving fast-rising investment and larger facilities. Conventional data centres typically require between 10 and 25 MW of power, while hyperscale AI data centres can exceed 100 MW (Hanwha Data Centers, 2025). As models capabilities expand and users' demand grows, so do these AI-oriented centres continue to grow in size. Their strong geographic concentration further strains local electricity grids because of their large and continuous power needs.

Data centres represent an increasing share in electricity consumption. In Ireland, data centres account for 20% of metered electricity demand (Ireland CSO, 2024). In the United States, data centres already exceed 10% of the electricity consumption in six states. Virginia is the US state with the largest share of electricity demand from data centres with 25% (Slok, 2024). Data centres running AI are expected to increase the electricity demand by even more. By 2030, data centres should represent about 30% of the electricity demand in Ireland.

Energy consumption also occurs during the hardware production for AI. However, energy for hardware production is generally lower than energy for operation. The most energy intensive stage of hardware production is chip manufacturing. The production of a 3-nm semiconductor wafer requires 2.3 MWh of electricity. For a high-performance server, total manufacturing energy exceeds 10 MWh. However, its energy consumption during five years of operation is more than 80 MWh (Garcia Bardon, et al., 2021). Around 60% of total manufacturing energy is connected to wafer fabrication and semiconductor processing, especially deposition, lithography, and etching, while the remaining 40% supports the manufacture of auxiliary systems such

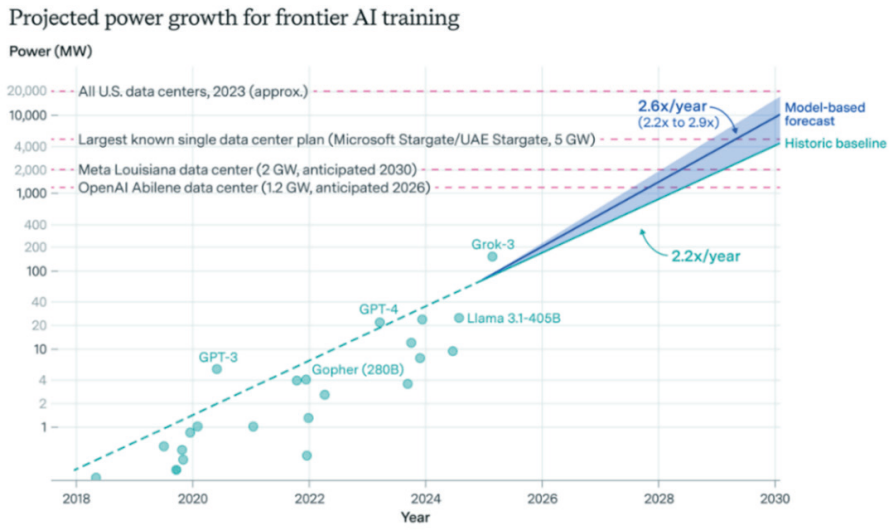
as water treatment and cooling.

Energy consumption increases with growing computational capacity. The manufacturing of more complex chips increases electricity consumption during fabrication, regardless of the manufacturing processes becoming more efficient. On the other hand, advanced chips increase the number of operations per unit, thus reducing the energy need per computation (Schneider, et al., 2025).

Chip production is mostly located in East Asia, with 70% of global production volume. The global chip production industry consumes more than 100 TWh of electricity annually, or 1% of the overall industrial electricity demand. For example, Taiwan Semiconductor Manufacturing Company (TSMC) used 20 TWh of electricity in 2023, which is equivalent to 10% of the total electricity consumption in Taiwan (Trueman, 2025). TSMC's electricity consumption could reach 24% of Taiwan's electricity consumption by 2030 as the industry moves towards the manufacture of advanced chips. Between 2016, when TSMC began producing 10-nm chips, and 2023 when the company shifted to the mass production of 3-nm chips, the electricity consumption of TSMC more than doubled (Trueman, 2025).

During training AI models learn statistical relationships from data in order to later generate predictions or actions aligned with defined objectives. In recent years, the scale of model training has increased exponentially. Estimates suggest that GPT-4 was trained using 5 trillion data points and 2.2×10^{25} calculations (Epoch AI, 2025).

Figure 3. Training power draw of AI models



Source: You et al, 2025

Training of AI models is time- and energy-intensive and relies on specialized hardware. Training of GPT-3 needed 5 MW of power and consumed approximately 1,287 MWh of electricity, which was responsible for the emission of more than 550 tonnes of CO_2, and required over 700,000 litres of cooling water (Rogers, 2024). GPT-4 was trained on 25,000 GPUs with a power need of 10 MW. Auxiliary IT equipment and cooling systems increased the total training power demand to 22 MW. GPT-4 was trained over 15 weeks, which returns a total energy consumption of 47,000 MWh, assuming an 85% power load factor (Ludvigsen, 2023).

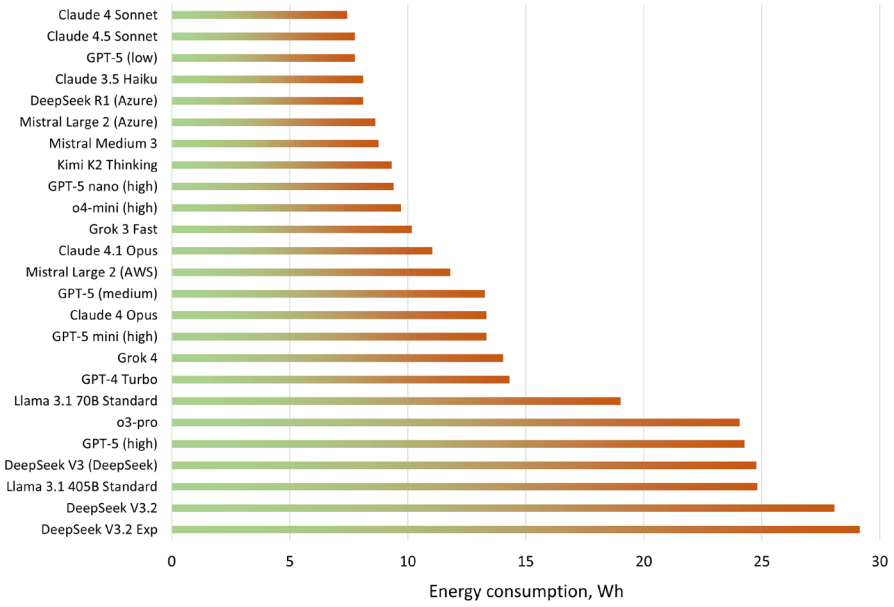
The power need for AI training increases 2.2 times per year. Recent training runs already exceeded 100 MW. Future power demand will depend on three factors: hardware efficiency, training duration, and computational scaling. Energy efficiency of AI GPUs has improved 40% per year, while the duration of AI model training increases by 10–20% per year as innovation cycles shorten. However, advanced chips require more computational expenses and the energy demand for advanced chips will continue to grow 4–5 times annually. Combining these three complimentary factors return an average power demand increase of 2.2–2.9 times per year, reaching between 4 and 16 GW by 2030 (Epoch AI, 2026).

The most power-intensive AI models for training are xAI's Grok 3 and Grok 4, trained in 2025 using 100,000 Nvidia H100 GPUs at the Colossus data centre in Memphis, Tennessee (Buntz, 2025). This facility uses a power capacity of 150 MW, illustrating the rapid growth in electricity and infrastructure demands associated with the most recent AI model training.

Each user query to an LLM model triggers energy and water consumption and is responsible for CO2 emissions. The energy demand per query depends on the AI model and its reasoning complexity, prompt length, and the employed infrastructure. Empirical benchmarking shows that short prompts require between 0.3 and 0.4 Wh of energy, while long prompts and reasoning intensive queries may need between 20 and 30 Wh of energy. This is a difference of more than 60 times between the most efficient and the most energy intensive prompts. Even small queries may lead to large energy demands when multiplied across millions of users. A short query with 1 Wh of energy demand, when multiplied across hundreds of millions of daily requests, can result in an annual electricity demand in excess of 100 GWh (Jengham, 2025). Although individual AI interactions appear negligible in terms of energy demand, LLMs at the system level need substantial physical resources and produce a measurable environmental impact.

The most energy intensive LLMs exceed 30 Wh per long prompt, whereas the most efficient ones require only 0.3 Wh. GPT-4 consumes 0.42 Wh for each, equivalent to 3.4 Wh daily for a user issuing eight queries. The estimated energy demand in 2025 was 400,000 MWh. Energy demand also depends on LLMs' reasoning depth. In GPT-5, the energy demand of medium queries ranges from 2.33 Wh to 17.15 Wh, and long queries can even reach 33.8 Wh (Jengham, 2025). The energy consumption of LLM models for a long query (10,000 input tokens and 1,500 output tokens) is shown in Figure 4. The equivalent of 1,500 tokens is approximately 1,000 words.

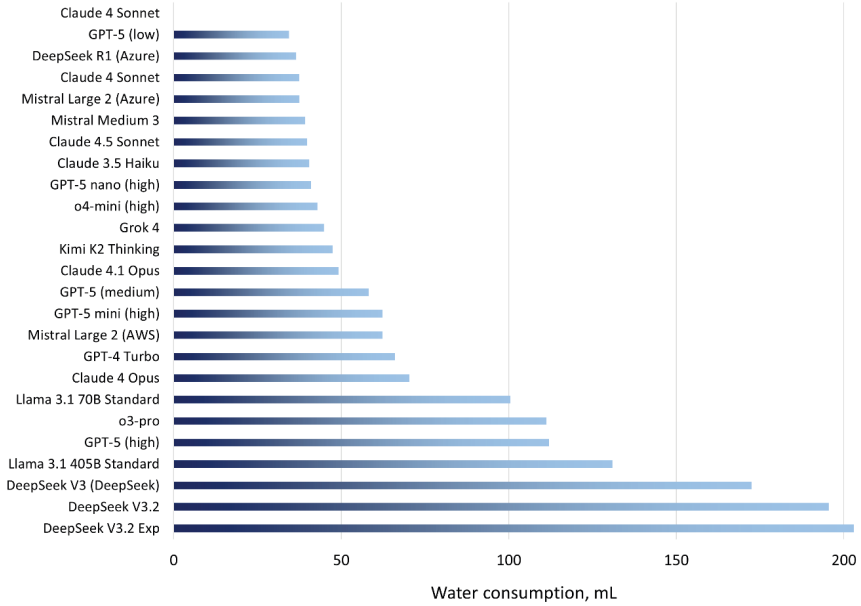
Figure 4. Energy consumption of LLM models for a long query (1,000 words output)



Source: Authors according to Jegham et al., 2025.

Water consumption of LLMs occur both during training and daily operation inference. During training, GPT-3 required more than 700,000 litres of cooling water which was lost into the atmosphere through evaporation in cooling towers. During daily operation, water consumption depends on the AI model and the employed infrastructure. Highly efficient systems use less than 4 millilitres (mL) per long prompt, while inefficient models such as DeepSeek R1 deployed on its own servers consumes 200 mL per query. Interestingly, DeepSeek R1 run on Microsoft Azure required only about 34 mL of cooling water. At the annual level, the operation of GPT-4 was responsible for 1.5 million m3 of evaporated freshwater (Herrera et al., 2025). The water consumption of LLM models for a long- query (10,000 input tokens and 1,500 output tokens) is shown in Figure 5.

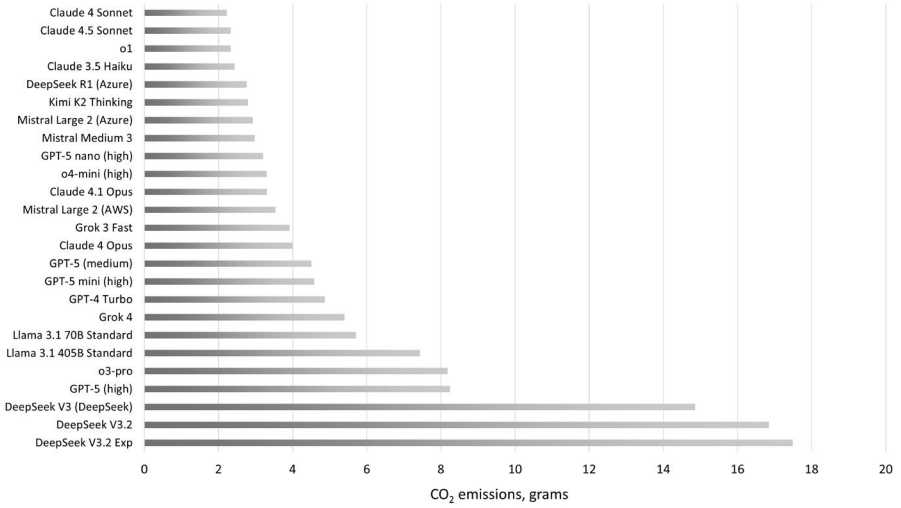
Figure 5. Water consumption of LLM models for a long query (1,000 words output)



Source: Authors according to Jegham et al., 2025

Carbon emissions from large language models arise during both training and inference. The training of GPT-3 alone generated more than 550 tonnes of CO_2-equivalent emissions. During inference, emissions vary widely depending on model efficiency and deployment context. Highly efficient systems emit less than 0.3 grams of CO_2 per long prompt, whereas DeepSeek-R1 running on its own infrastructure produces more than 17 grams per long query. When deployed on Microsoft Azure, emissions fall to approximately 2.5 grams per query, representing a reduction of about 85 percent. At scale, projected annual emissions from GPT-4o inference reach roughly 138,125–163,441 tonnes of CO_2e per year. For GPT-5, the reported impacts are 24.27 Wh of energy per long query, 112.07 mL of water consumption, and 8.25 g CO_2e emissions (Shilov, 2025). The CO_2 emissions of LLM models for a long-form query (10,000 input tokens and 1,500 output tokens) are shown in Figure 6.

Figure 6. CO_2 emissions of LLM models for a long query (1,000 words output)



Source: Authors according to Jegham et al., 2025

US AI-related data centre power capacity is estimated at roughly 5 GW today and could exceed 50 GW by 2030. In the near term, AI is the primary driver of data centre electricity growth, supported by hyperscalers capital expenditure surpassing USD 370 billion in 2025. Planned large-scale facilities, including OpenAI's 1.2 GW Stargate project and Meta's Louisiana campus exceeding 2 GW, illustrate the scale of expected expansion (OpenAI, 2025). Although broader economy-wide electrification may ultimately generate even larger electricity demand, it implies different requirements for power-system development than AI-driven load growth. Projections indicate that AI could account for more than 5% of USA electricity generation capacity by 2030. Power requirements for single frontier training runs may approach the output of large power plants, highlighting the need for new approaches to grid planning, permitting, and infrastructure investment.

In 2024, data centres consumed 415 TWh of electricity globally, or 1.5% of world electricity consumption. The regional split is highly skewed: the United States accounted for 50% of global data centre electricity consumption in 2024, China 25%, and Europe 15%. In the IEA base scenario, global data centre electricity consumption will increase to 945 TWh by 2030, representing 3% of global electricity consumption in 2030. The alternative scenarios span across a wide range: from 670 TWh in the headwinds scenario to 1260 TWh in the Liftoff scenario. After 2030, uncertainty increases and the possible range widens. By 2035, the range will span from 700 TWh to 1720 TWh across the four scenarios (IEA, 2025).

In the United States, data centres account for nearly half of electricity demand growth between now and 2030. By the end of the decade, US electricity use for data centres will exceed the electricity used for producing aluminium, steel,

cement, chemicals and other energy-intensive goods combined. The IEA decomposes demand growth into server stock, server wattage, utilization, idle power and supporting infrastructure. In the base scenario, total installed data centre capacity will increase from 100 GW to 225 GW in 2030 (IEA, 2025).

Electricity consumption in AI-driven accelerated servers is projected to grow by 30% annually in the base scenario, while conventional server electricity consumption around 9% annually. Accelerated servers will account for almost half of the net increase in global data centre electricity consumption by 2030, while conventional servers for 20%. Other IT equipment accounts for around 10% of the net increase and the cooling/other infrastructure for around 20%.

Power Usage Effectiveness (PUE) is a standard metric used to measure data centre energy efficiency, defined as the ratio of total facility energy consumption to the energy used by IT equipment alone (servers, storage, and networking). A PUE equal to 1.0 represents an ideal case where all incoming power is used by the IT hardware, with additional needs for cooling, lighting, or power distribution. In real facilities, PUE values are larger than 1, because the additional infrastructure consumes energy to support operation. Modern, high-efficient hyperscale data centres achieve lower PUE values (1.1–1.3), while older or less optimized facilities operate at PUE values of 1.5–2.0 (IEA, 2025).

Global weighted average PUE will improve from 1.41 in 2024 to 1.29 by 2030 in the base scenario. This is roughly a 30% reduction in cooling requirements per unit of IT electricity used. Yet total electricity demand still rises because the IT load expands rapidly. Meeting the additional electricity demand requires both low-emissions and dispatchable supply. In the base case, renewables meet half of the global growth in data centre demand, adding over 450 TWh to 2035. Natural gas generation for data centre demand increases by 175 TWh to 2035, mostly in the United States. Nuclear contributes about the same amount of additional generation, notably in China, Japan and the United States, with the first small modular reactors (SMRs) expected to come online in 2030 (IEA, 2025).

3 Cooling of AI

Most data centres still rely on air-based cooling, but rapid increase in rack density are pushing the transition toward liquid cooling. Traditional date centres use computer room air conditioners (CRAC) to circulate chilled air through hot and cold aisles. These systems typically support rack power densities of about 5-15 kW, and in hyperscale data centres up to 20-30 kW per rack. At higher computational densities, when rack loads exceed 30 kW, air cooling becomes insufficient, which creates thermal risks, increased energy consumption, and deployment constraints. Liquid cooling therefore emerges as the next-generation solution because water cooling achieves higher heat transfer coefficients than air cooling systems. Single phase liquid cooling achieves up to 50 kW/m2, liquid immersion cooling up to 100 kW/m2, and two-phase cooling achieve more than 100 kW/m2 (Gebrael et al., 2022).

The development of cooling systems for data centres offers new opportunities

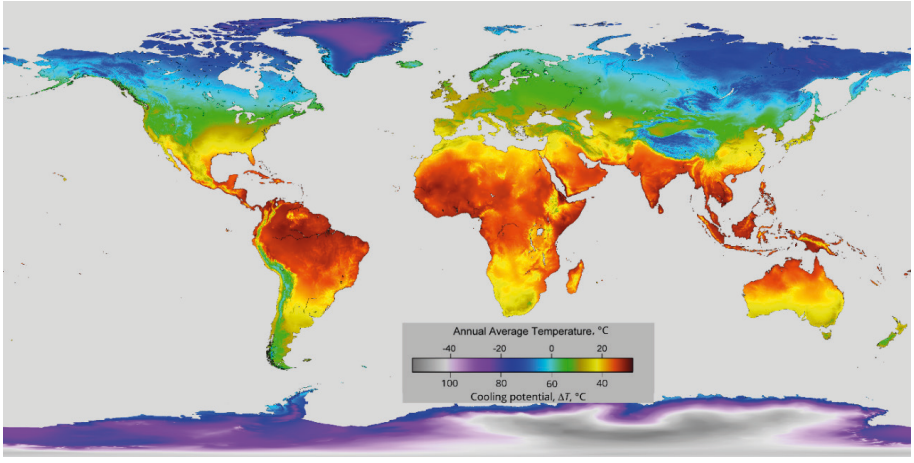
for heat recovery and carbon reduction. Liquid cooled data centres can deliver return water temperatures near 60 °C, supporting efficient liquid-to-liquid heat reuse and reducing thus the heating demand of buildings (Blecich et al., 2024).

Ambient conditions affect the cooling performance, the energy efficiency, and the technological configuration of modern data centres. Cooling capacity is limited by the temperature gradient between the IT equipment and the surrounding air used as the heat sink. As ambient temperature increases, the cooling potential reduces, which limits the availability of free cooling modes, and lowers the performance of heat rejection systems. Higher outdoor temperatures increase the compressor work in heat pumps, which increases the electricity consumption and reduces the overall performance of the cooling equipment. In contrast, low ambient temperatures enhance passive cooling and extend the operation of air-side or water-side economizers, substantially improving the overall efficiency (Kirinčić et al., 2025).

Cold and temperate regions, such as Northern Europe, Canada, and Nordic countries, allow for longer periods of free cooling, reduced chiller runtime, and lower power consumption. Conversely, hot and humid climates, common in desert and tropical regions, experience limited free cooling potential and higher wet bulb temperatures. This limits the performance of wet cooling towers and prolongs the dependence on mechanical refrigeration, resulting in higher energy demand, water consumption, and operational cost.

Climate directly shapes cooling-technology selection: economizer-based air cooling dominates in cold regions; hybrid free-cooling and chiller systems prevail in temperate zones; evaporative and liquid-assisted cooling are required in hot-dry environments; and chilled-water plus direct liquid cooling becomes essential in hot-humid climates.

Figure 7. Worldwide annual average air temperature for data centres cooling potential



Source: Authors

Waste heat recovery from data centres is finding increasing application aiming to reduce reliance on conventional fossil fuels and improving overall energy efficiency. The emerging applications for date centre waste heat utilization are:

- district heating integration,
- on-site building heating,
- campus heat reuse,
- industrial and agricultural waste heat reuse.

Waste heat utilization is already implemented in real data centres. District heating integration is used in Stockholm, where waste heat from data centres is used in local district heating networks, in combination with heat pumps for additional heating.

In Tallaght, Ireland, an AWS data centre supplies 3 MW of heat to a district heating scheme. Hot air from the servers is captured by a heat exchanger inside which water is heated to 25 °C. This water then passes through two heat pumps in series, first raising its temperature to about 45 °C, and then further increasing it to 80 °C, before being distributed through the district heating system to public buildings (SEAI, 2025). This system reduces the CO2 emissions by 1,500 tons per year. Studies estimate nearly 1000 EU data centres are within sensible distance to district heating networks, meaning their waste heat could be leveraged for community heat demand. Municipal projects in Brunswick, Germany, are featured in the ReUseHeat project, demonstrating waste heat recovery from data centres feeding into the local heating infrastructure.

The Aquasar project at the Federal Institute of Technology (ETH) in Zürich is a well-known early implementation where waste heat from the liquid-cooling system is reused to heat campus buildings. The Aquasar supercomputer uses on-chip liquid cooling with micro-channel cold plates mounted directly on the processors, where most heat is generated. Water flows through micro channels at around 60 °C, leveraging its very high heat capacity and thermal conductivity to remove heat more efficiently than air and to keep processor temperatures safely below their maximum limit of 85 °C (Zimmermann, 2012).

Waste heat from data centres is also used for mixed industrial and agricultural reuse. Innovative waste heat recovery includes heating of greenhouses, fish farms, animal farms, and aquaculture. The Green Mountain Data Centre in Norway use an 8 °C fjord water to cool servers, heating it up to 20 °C and supplying to land-based lobster farming to maintain the ideal 20 °C water temperature for optimal lobster growth (Green Mountain, 2025).

4 CO_2 emissions of AI

Fossil fuels remain central for running data centres in the near term. Natural gas and coal are expected to meet 40% of the additional electricity demand for data centres until 2030. In the liftoff scenario, between 2024 and 2030, about 50% of additional electricity generated for data centres will come from fossil

fuels. Recent data show significant regional variation in the carbon intensity of electricity generation. In 2024, the United States averaged roughly 384 gCO_2/kWh, reflecting continued growth in renewables and declining coal use. Electricity in China is more carbon-intensive, with an average of 500 gCO_2/kWh in early 2025 as clean energy expands. In contrast, the EU-27 achieved 213 gCO_2/kWh in 2024, among the lowest levels for major economies due to the high shares of renewables and nuclear power (FAIST Group, 2025). The global average carbon intensity of electricity generation is estimated at 450 gCO_2/kWh of electricity produced worldwide. Taking that the United States accounted for 50% of global data centre electricity consumption in 2024, China 25%, Europe 15%, and rest of the world 10%, the average weighted carbon intensity of electricity for data centres was around 400 gCO_2/kWh. Since data centres consumed 415 TWh of electricity globally in 2024, the CO_2 emissions from electricity consumed in data centres were around 170 Mt in 2024 (IEA, 2025). The CO_2 emissions from electricity generation for data centres will reach 320 Mt by 2030, then decline to around 300 Mt by 2035 because of the larger share of nuclear and renewable energy in electricity generation for data centres. In the base scenario, the CO_2 emissions from electricity for data centres will grow almost 90% by 2030, reaching 1% of global combustion emissions (IEA, 2025).

The report's regional supply mix numbers illustrate why emissions trajectories differ. In the United States, natural gas currently provides over 40% of electricity for data centres, renewables about 24%, and nuclear and coal roughly 20% and 15% respectively. Between 2024 and 2030, natural gas adds over 130 TWh of annual generation to meet data centre demand, while renewables add about 110 TWh. In China, electricity for data centres is dominated by coal at around 70%, with renewables nearly 20% and nuclear close to 10%. Between 2024 and 2030, both coal and renewables add about 90 TWh in China. These figures show why near-term AI expansion can increase fossil utilization even if long-term plans emphasize clean power (IEA, 2025).

Artificial intelligence is increasingly applied across the energy system to improve efficiency and reduce emissions. Currently, AI optimization of processes is lowering energy demand and emissions in fuel and mineral supply, power generation, industry, transport, and buildings. Examples include methane-leak detection in oil and gas operations, efficiency improvements in fossil-fuel power plants, energy-optimized industrial processes such as cement production, more efficient vehicle routing and driving behaviour yielding 5–10% fuel savings and building energy-management systems capable of reducing consumption by around 10%. Despite these benefits, the aggregate emissions impact of AI remains modest. Future reductions will depend on the scale of adoption, shaped by affordability, regulatory support, digital infrastructure, and advances in AI capability. The trajectory of these enabling factors, and thus AI's long-term emissions effect, remains uncertain.

Widespread deployment of AI across end-use sectors could reduce global emissions by approximately 1.4 Gt CO_2 in 2035. This potential reduction, excluding any future AI-driven technological breakthroughs, would be three times larger than projected data-centre emissions in the lift-off scenario and nearly five times those in the base scenario. In industry, one-third of AI-enabled emissions reductions arise from process improvement, particularly in energy-intensive sectors where digitalization enables efficiency gains. The remaining

two-thirds derive from indirect electricity-demand reductions, especially in light industry, with higher savings in digitally advanced subsectors such as transport equipment and machinery. Optimization of road transport and autonomous driving contribute to the emissions reductions in transport.

Despite the technical potential of AI for reducing CO_2 emissions, barriers still exist. These barriers are related to limited access to datasets, underdeveloped digital infrastructure, regulatory constraints, and institutional challenges. These barriers mean that the potential for CO_2 emissions reduction through the implementation of AI methods could be limited.

5 Investment in AI

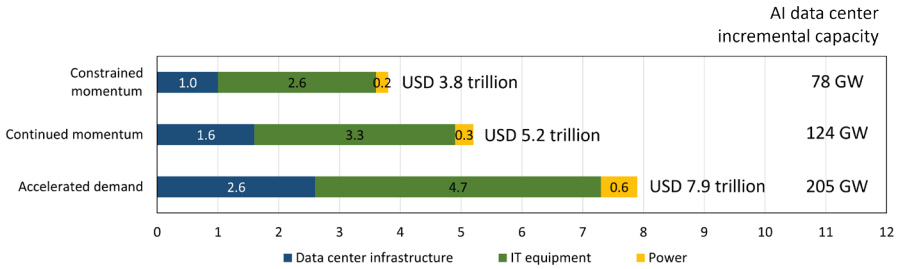
Capital investment in AI is growing fast. The IEA estimates that the annual global investment in data centres increased from USD 100 billion in 2015 to USD 500 billion in 2024. In the base scenario, annual investment will exceed USD 800 billion by 2030. The cost structure is dominated by the IT infrastructure. The capital expenditure (capex) is divided into IT capex (servers, networking, memory, storage), nonIT capex (buildings, cooling, transformers, UPS) and energy capex. IEA reminds that investment in additional generation capacity and grid lines is marginal relative to the spending on data centre IT and nonIT equipment. In other words, data centres are more capital intensive than energy intensive, meaning that the total power costs are still low even though electricity demand becomes material.

Hyperscaler accelerated-server investment grew from around USD 4 billion in 2015 to nearly USD 100 billion in 2024. The report notes that major technology firms earmarked over USD 300 billion in capex in 2025, primarily for data centres and IT procurement. A further structural feature is turnover: IT equipment becomes obsolete in 4-6 years after installation, whereas a transformer typically lasts around 30 years (IEA, 2025).

Regional investment is concentrated. In the base case, cumulative data centre investment in the United States amounts to about USD 2.4 trillion by 2030 (more than 5% of total fixed capital investment over the period). China sees cumulative data centre investment of about USD 1.3 trillion to 2030 (just over 2% of total fixed capital investment in that period). The rest of the world amounts to about USD 1 trillion (IEA, 2025)

Generative AI could add trillions of dollars in annual economic value. Generative AI is estimated to contribute between USD 2.6 trillion and USD 4.4 trillion per year. The total annual capital investment in AI data centres could reach between USD 3.8 trillion and USD 7.9 trillion (Noffsinger et al., 2025). This quantity of capital investment could establish generative AI not as a marginal efficiency tool but as a foundational driver of global economic growth. About 75% of the potential value comes from customer operations, marketing and sales, software engineering, and research and development. These domains share common properties: heavy reliance on language, knowledge processing, creative and analytical workflows, all of which are areas where generative AI is rapidly advancing.

Figure 8. Capital investment in AI data centres by 2030



Source: Noffsinger et al., 2025

Productivity gains due to the implementation of generative AI are estimated up to 30–45% in customer operations, 5–15% in marketing, 3–5% in sales, 20–45% in software engineering, and 10–15% in research and development. Early adoption of generative AI in these areas will likely result with highly competitive advantages. Generative AI will reshape jobs rather than automate jobs. Current technologies could automate activities consuming 60–70% of the employees working time, largely because LLMs' capabilities extend the automation into knowledge work previously considered resistant to technological substitution (McKinsey & Company, 2023). Productivity growth ensured by generative AI will depend on the investment in skills and workforce transition. However, realizing these gains requires reskilling, occupational mobility, and institutional adaptation to manage risks and ensure economic benefits.

The transformative potential of generative AI is still emerging. While the early use of generative AI show promising results, further development will depend on responsible use, redesigned business practices, and sustainable growth of job capacities. The long-term impact of generative AI will depend on the organizational and societal responses as well as on the technical progress.

Today, data centres and AI now compete for critical minerals with clean energy technologies: copper and aluminium for power distribution, rare earths for magnets, lithium for batteries and uninterruptible power supplies, silicon and gallium for semiconductors and power electronics (Bisht et al., 2023). The IEA estimates that mineral demand from projected data centre capacity expansion in 2030, as a share of total demand in 2024, could reach up to 2% for copper and silicon, over 3% for rare earth elements and 11% for gallium. In absolute terms, this corresponds to 512 kilotons of copper and 75 kilotons of silicon in 2030.

The supply of critical minerals is geographically concentrated, and export controls have become more frequent in recent years. Supply concentration magnifies vulnerability. In 2024, nearly 60% of refined copper supply, around 90% of aluminum and over 90% of silicon, magnet rare earths and gallium originated from the top three producing countries.

6 Conclusions

Artificial intelligence is often perceived as a purely digital or immaterial technology. The analysis presented in this paper demonstrates the opposite: AI is a rapidly expanding industry that is linked to critical material, manufacture capacities, electricity generation, cooling infrastructure, capital investment. Global data-centre electricity consumption will increase from 415 TWh in 2024 to 945 TWh by 2030 and 1,200 TWh by 2035, while annual investment will surpass USD 800 billion before 2030 and cumulative investment will exceed USD 4 trillion. Associated indirect emissions increase from 180 Mt CO_2 in 2024 in the near term, even if longer-term stabilization occurs as low-carbon electricity expands. At the same time, data-centre growth requires substantial material inputs, including significant shares of global copper, silicon, and gallium supply, highlighting emerging resource dependencies.

Beyond aggregate electricity demand, the analysis shows that AI lifecycle impacts are dominated by large-scale inference and infrastructure operation, while training energy, though substantial, represents only one component of the overall footprint. Cooling technologies, geographic siting, and electricity-generation mix therefore have become decisive determinants of AI's environmental intensity. The coexistence of rapid efficiency improvements and exponential demand growth implies that total resource consumption can continue rising even as individual systems become more efficient.

AI also presents a mitigation potential for CO_2 emissions. The widespread use of AI applications across end-use sectors could enable emissions reductions on the order of 1.4 Gt $CO_2$by 2035, exceeding the projected emissions of data centres in several scenarios. However, realizing this potential depends on the digital infrastructure, regulatory frameworks, data availability, and organizational adoption, all of which remain uncertain. All together, these findings suggest that the real price of AI will be determined not only by the computational progress but also by energy decarbonisation, material supply, and the availability of infrastructure. Future research and policy should treat AI as a core component of the industrial transformation, rather than a digital service, ensuring that its expansion aligns with climate and resource sustainability.

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Does AI Preparedness Alter the Sustainability Costs of Economic Disasters?

Original scientific paper

Lena Malešević Perović[1]

ABSTRACT

This paper examines whether countries' preparedness for artificial intelligence (AI) conditions the impact of economic disasters on sustainable development. The purpose of this study is to investigate the role of AI preparedness in shaping countries' resilience to economic disasters. The objective of the study is to empirically assess how economic disasters affect sustainable development outcomes and whether these effects differ across countries with different levels of AI preparedness. Building on the peak-to-trough disaster identification framework, we analyse a cross-country panel covering major economic disasters, including the COVID-19 shock, and three complementary sustainability indicators: adjusted net savings, the Human Development Index, and the SDG Index. AI preparedness is measured using the IMF Artificial Intelligence Preparedness Index and treated as a structural, time-invariant country characteristic. We estimate two-way fixed-effects panel models with country and year fixed effects and clustered standard errors, distinguishing between disaster onset and disaster duration to capture dynamic adjustment processes. The results confirm that economic disasters are associated with significant short-run losses in economic and social dimensions of sustainable development. Contrary to a simple resilience narrative, AI preparedness does not systematically mitigate these losses. Instead, higher AI preparedness is associated with sharper short-run declines in human development at disaster onset, consistent with faster but socially costly adjustment dynamics. No significant moderating effects are found during prolonged disaster periods. Overall, the findings suggest that AI preparedness shapes the timing rather than the direction of sustainability impacts following economic disasters. Digital readiness alone does not provide immediate protection against sustainability losses and should be complemented by social and labour-market policies to support inclusive and resilient development paths.

Keywords: *Economic disasters, Artificial intelligence preparedness, Sustainable development*

JEL classification: *O33; Q01; E61; H12*

1 *Full professor, University of Split, Faculty of Economics, Business and Tourism, Cvite Fiskovića 5, 21000 Split, Croatia, Phone: +385 21 430 732 E-mail: lena@efst.hr*

1 Introduction

Recent global crises, especially the COVID-19 pandemic, have highlighted the relationship between digital transformation, economic resilience, and sustainable development. As noted by Jaumotte et al. (2023), the pandemic accelerated digitalisation, which, in turn, improves economic resilience could potentially increase productivity in the longer term. Higher productivity enhances economic capacity, enabling greater investment in public services, social programmes, and environmental objectives, thereby ultimately supporting sustainable development outcomes (Barro and Sala-i-Martin, 2004). However, the relevance of digital transformation for sustainable development becomes particularly salient during periods of severe economic stress, when development gains are most at risk of reversal.

Major macroeconomic shocks, such as the Global Financial Crisis of 2008/2009, the COVID-19 pandemic, and recent geopolitical disruptions, demonstrate that economic disasters – distinguished from other crises by their severity and persistence – constitute an especially troublesome form of shock with the capacity to reverse progress towards the United Nations Sustainable Development Goals (SDGs). Economic disasters are characterised by deep output losses (exceeding 10%), prolonged recovery periods, and substantial disruptions to labour markets, public finances, and institutional capacity (Ćorić, 2021). As documented by Malešević Perović and Ćorić (2024a; 2024b), such disasters generate persistent and multidimensional adverse effects on sustainability outcomes, extending well beyond short-term economic contractions.

Within this context of heightened exposure to economic disasters, the recent period has also been marked by the rapid spread of artificial intelligence (AI), which is increasingly transforming economic and social systems. AI comprises a broad set of technologies described as self-learning and adaptive systems capable of processing large volumes of data and supporting complex decision-making. As noted by the United Nations (2026), “in all these spheres and more, AI has significant potential to support the United Nations by promoting inclusivity, reducing inequalities, helping to accelerate nearly 80% of the Sustainable Development Goals (SDGs), and strengthening the work of the United Nations system.” This potential reflects the fact that AI is increasingly embedded in the economic processes underlying sustainable development, including resource allocation, economic responses to shocks, and the design and implementation of public policy. By improving economic forecasting, enabling real-time data analysis, and supporting evidence-based policy decisions, AI contributes to information flows and adaptive capacity, essential for achieving long-term sustainability objectives (EPALE, 2026). Crucially, the extent to which these potential benefits materialise does not depend on the mere presence of AI technologies, but on countries’ underlying preparedness to adopt, govern, and integrate AI into economic and institutional systems.

Despite the rapidly growing literature on digital transformation and artificial intelligence, the interaction between AI preparedness and the macroeconomic consequences of economic disasters remains insufficiently explored. Existing studies investigate either the economic effects of artificial intelligence and

digitalisation (e.g. Arsić, 2020; Cannavale et al., 2024) or the macroeconomic consequences of large economic disasters (e.g. Barro & Ursúa, 2008; Malešević Perović & Ćorić, 2024a; 2024b). However, these two strands of literature have largely evolved independently. As a result, there is limited empirical evidence on whether countries' preparedness for artificial intelligence affects how economies experience and adjust to severe macroeconomic shocks and their sustainability implications. By addressing this gap, the paper contributes to the literature by providing new empirical evidence on whether countries' preparedness for artificial intelligence shapes the sustainability consequences of severe economic disasters.

Based on this research gap, the paper tests the following hypotheses.

> **H1**: Economic disasters are associated with a deterioration in sustainable development outcomes.
>
> **H2**: Countries' preparedness for artificial intelligence influences how economic disasters affect sustainable development outcomes.

This paper builds directly on the literature on economic disasters and sustainable development, particularly Malešević Perović and Ćorić (2024a; 2024b), and extends it in two important directions. First, the empirical analysis is updated to include the most recent period of global economic turbulence, encompassing the COVID-19 shock and its aftermath, which could not be examined in studies prior to the ending of 2019. Second, the paper introduces a new dimension by incorporating countries' preparedness for artificial intelligence – measured by the IMF AI Preparedness Index – into the relationship between economic disasters and sustainable development. This allows for an explicit assessment of whether digital readiness conditions the sustainability consequences of severe economic contractions.

The paper makes two main contributions. First, it introduces a novel analytical perspective by examining how countries' preparedness for artificial intelligence influences the sustainability impacts of economic disasters, rather than treating digital transformation and macroeconomic shocks as separate phenomena. The analysis shows that AI preparedness affects the timing of sustainability losses during economic disasters. Second, the paper demonstrates that digital preparedness is an important structural feature influencing how countries adjust to economic disasters. The results indicate that countries with higher AI preparedness tend to adjust more quickly, which can increase short-term social costs even if longer-term development prospects are not necessarily worse. Thus, the paper shifts attention from whether economies absorb shocks to how they adjust when shocks occur.

The remainder of the paper is structured as follows. Section 2 reviews the literature. Section 3 outlines the methodology. Section 4 describes the data. Section 5 presents the empirical results and discusses their interpretation and implications, while Section 6 concludes.

2 Literature review

Although a growing body of research examines economic disasters, artificial intelligence, and sustainable development separately, their interaction has received limited systematic empirical attention. This paper therefore builds on and connects several closely related strands of research—economic disasters and sustainability, crisis persistence, and AI-enabled resilience—in order to motivate and position its empirical analysis.

Malešević Perović and Ćorić (2024a) show that the adverse effects of economic disasters on sustainable development are substantially larger and more persistent than those associated with standard economic crises. Using a large cross-country panel and multiple aggregated sustainability indicators—including adjusted net savings, the Human Development Index, and the SDG Index—they document that sustainability indicators continue to deteriorate even after the disaster episode formally ends. These findings suggest that severe macroeconomic shocks can permanently alter development trajectories rather than merely generate temporary setbacks.

Malešević Perović and Ćorić (2024b) provide comprehensive evidence on the multidimensional sustainability effects of economic disasters by jointly analysing economic, social, and environmental indicators across countries at different levels of development. They find that economic disasters significantly reduce adjusted net savings and human development, disproportionately affecting low- and lower-middle-income countries, while also exerting heterogeneous effects across environmental dimensions. While some environmental pressures temporarily ease during disasters due to reduced economic activity, broader sustainability outcomes deteriorate in the long run, highlighting the fragility of sustainability commitments during periods of severe economic stress.

In parallel, a growing literature examines the role of AI in addressing large-scale societal challenges, particularly in the context of climate change, public health crises, and sustainable development. Zhang, Hu and Fang (2025) find that countries in Asia and the Pacific face severe multi-hazard climate risks, with projected GDP losses of up to 17% by 2070 and 41% by 2100 under high-emissions scenarios, reinforcing climate change as a key driver of poverty and inequality. The authors argue that AI can accelerate climate mitigation and adaptation through improved data access, modeling, and decision-making, but emphasise the AI's dual role as both an enabler of climate action and a source of significant energy, water, and resource pressures. Uneven AI readiness across countries and communities may therefore exacerbate existing inequalities in climate resilience, particularly in net-zero transitions, adaptation, and disaster risk reduction.

Șerbu and Mârza (2024) examine the role of artificial intelligence within a broader sustainable development framework, arguing that AI-driven innovation can act as a catalyst for post-crisis and post-war reconstruction by enhancing productivity, supporting evidence-based policymaking, and accelerating progress toward the Sustainable Development Goals. Focusing on transformational change rather than purely technological adoption, the authors emphasise that AI's developmental impact depends critically

on institutional capacity, governance quality, and the integration of digital technologies into sustainability-oriented strategies. The research highlights the AI's potential to support resilience and recovery in disrupted economies, while cautioning that without appropriate regulatory frameworks and alignment with SDG priorities, technological innovation alone is insufficient to deliver inclusive and sustainable outcomes.

Related evidence from the public health literature further illustrates both the potential and the limitations of AI during large-scale shocks. Sharmin et al. (2025) show that AI-based models substantially improved outbreak forecasting, healthcare resource allocation, and vaccine distribution during the COVID-19 pandemic, achieving high predictive accuracy and reducing disparities in vaccine coverage. At the same time, the authors emphasise ethical challenges related to data privacy, algorithmic bias, and governance, arguing that effective AI deployment requires strong institutional frameworks. Similarly, Mhlanga (2022) documents how AI-supported digital technologies enhanced crisis response through improved disease surveillance, telemedicine, and accelerated vaccine and drug development, while highlighting that the benefits were unevenly distributed and constrained by data availability, institutional capacity, and persistent social inequalities.

Cheshmehzangi and Su (2025) analyse how AI transformed public health policymaking during the COVID-19 crisis, highlighting its role in enabling real-time data analysis, predictive modeling, coordinated decision-making, and more efficient resource allocation. While AI-supported governance facilitated faster and more targeted interventions, the study emphasises that outcomes remained shaped by institutional readiness, data quality, and ethical challenges related to privacy and equity. These findings suggest that AI enhances the speed and coordination of crisis responses, but does not eliminate structural vulnerabilities or guarantee equitable social outcomes.

More broadly, Rosen (2025) discusses AI as a potentially transformative enabler of sustainable development, arguing that it can accelerate progress toward the Sustainable Development Goals by improving productivity, decision-making, and early-warning capabilities across economic, environmental, and social domains. However, the author stresses that AI's contribution to sustainability is contingent on governance quality, data availability, institutional capacity, and inclusive deployment, particularly in developing and structurally vulnerable countries. Similarly, Korang (2025) reviews crisis management and resilience-building lessons from recent global events and cautions that technological adoption alone does not ensure resilience, as many systems remain vulnerable due to insufficient preparedness, unequal resource distribution, and an excessive focus on short-term recovery rather than long-term adaptive capacity.

Finally, Gohr et al. (2025) provide a comprehensive review of artificial intelligence applications in Sustainable Development Goals – related research, analysing 792 peer-reviewed studies across disciplines and policy domains. While documenting rapid growth in AI use—particularly in forecasting, system optimisation, and environmental applications—the authors identify a substantial misalignment between advanced AI methods and the social and institutional dimensions of sustainability. AI applications remain heavily

concentrated in technical domains, whereas poverty reduction, inequality, and institutional quality are comparatively underrepresented. The review also highlights pronounced geographic asymmetries in AI-driven sustainability research, reflecting uneven technological and analytical capacities across countries. Moreover, a substantial share of the empirical literature on artificial intelligence and sustainability operates at the firm or sectoral level, focusing on productivity, innovation, or environmental performance, whereas evidence at the national level—particularly on how AI preparedness interacts with large macroeconomic shocks and long-run sustainable development outcomes—remains scarce.

Despite these advances, the existing literature remains fragmented. While the disaster literature documents the persistent adverse effects of economic disasters on sustainable development, and the AI literature highlights the importance of technological and institutional readiness, empirical work has not yet examined whether AI preparedness systematically conditions the sustainability effects of economic disasters at the country level.

Taken together, the existing literature suggests that both the severity of macroeconomic shocks and countries' technological and institutional capabilities may influence development outcomes during periods of crisis. In particular, the disaster literature shows that severe economic shocks can generate persistent sustainability losses (Malešević Perović & Ćorić, 2024a; 2024b), while the emerging literature on artificial intelligence highlights its potential role in supporting sustainable development and improving decision-making in complex policy environments (Rosen, 2025). At the same time, studies on AI-enabled crisis management indicate that digital and AI-related capabilities may influence how societies respond to large-scale disruptions (Mhlanga, 2022; Sharmin et al., 2025; Cheshmehzangi & Su, 2025). This provides a conceptual basis for examining whether countries' preparedness for artificial intelligence may shape the sustainability consequences of economic disasters.

This paper contributes to the literature by explicitly linking these strands. By empirically analysing how pre-existing AI preparedness moderates the impact of economic disasters on sustainable development outcomes, it extends the disaster literature beyond average effects and embeds AI readiness within a macroeconomic shock framework.

3 Methodological approach

The empirical analysis uses a peak-to-trough economic disaster identification framework based on the rare-disaster literature (Barro, 2006; Barro & Ursúa, 2008), as operationalised and extended by Ćorić (2021), and later applied in Malešević Perović and Ćorić (2024a; 2024b). This framework is designed to identify severe macroeconomic contractions that exceed standard economic crises.

Economic disasters are identified using real GDP per capita series (the data sources used to construct these series are described in Section 4). Following Barro (2006) and Barro and Ursúa, (2008), a disaster episode is defined as

a cumulative decline of at least 10 per cent relative to the previous historical peak. This threshold ensures that only large and persistent contractions are classified as disasters, excluding mild or short-lived downturns. The peak-to-trough approach allows for transparent identification of both the magnitude and the duration of economic disasters and has been shown to perform well in cross-country settings (Ćorić, 2021).

Based on the identified disaster episodes, two binary indicators (dummy variables) are constructed. The first captures the duration of an economic disaster and takes the value of one for all years between the peak and the trough of a disaster episode (ED_duration). This variable reflects prolonged periods of severe economic stress, during which fiscal constraints, labour market disruptions, and social pressures are likely to persist. The second indicator captures disaster onset (ED_onset) and takes the value of one only in the first year of each disaster episode. This variable isolates the immediate impact of the shock and the initial adjustment phase.

Distinguishing between disaster onset and disaster duration is central to the dynamic adjustment framework, as short-run responses may differ substantially from longer-run adaptation processes (Malešević Perović & Ćorić, 2024a). Estimating separate specifications for each indicator allows us to examine how AI preparedness relates to different stages of economic disasters, distinguishing between short-run adjustment costs and longer-term resilience.

The baseline empirical model is estimated using a two-way fixed effects panel regression framework and can be expressed as:

$$SD_{it}=\alpha_i+\lambda_t+\beta_1 ED_{it}+\beta_2 AIP_i+\beta_3(ED_{it}\times AIP_i)+\varepsilon_{it} \quad (1)$$

where denotes sustainable development outcomes in country i and year t. Following Malešević Perović and Ćorić (2024a; 2024b), three alternative measures of sustainable development are considered in turn: adjusted net savings (ANS), the Human Development Index (HDI), and the SDG Index. These indicators capture economic, social, and composite dimensions of sustainability, respectively. Country fixed effects () control for time-invariant characteristics such as geography, historical institutions, and long-run development paths, while year fixed effects () capture global shocks and common trends affecting all countries in a given year, including international financial conditions and global policy responses.

The variable represents the economic disaster indicator, defined alternatively as disaster duration (ED_duration) or disaster onset (ED_onset). AI preparedness () is measured using the IMF Artificial Intelligence Preparedness Index and treated as a time-invariant country characteristic. The interaction term () captures whether AI preparedness conditions the effect of economic disasters on sustainable development outcomes. Since AI preparedness is treated as time-invariant, its main effect is absorbed by country fixed effects. As a result, identification comes from the interaction term. Standard errors are clustered at the country level to account for serial correlation and

heteroskedasticity, in line with best practice in panel data analysis.

AI preparedness is measured using the IMF AI Preparedness Index, which is currently available for a single reference year - 2023. The index reflects slow-moving structural characteristics related to digital infrastructure, human capital, innovation capacity, and institutional and regulatory frameworks (International Monetary Fund, 2023). Given its construction and temporal availability, AI preparedness is treated as time-invariant in the empirical analysis. This approach is consistent with interpreting AI preparedness as a latent structural capacity rather than a short-term policy variable, and mirrors common practice in the literature when analysing institutional or structural characteristics that evolve gradually over time. To facilitate interpretation and comparability across specifications, the AI Preparedness Index is standardised prior to estimation. Interacting AI preparedness with the disaster indicators allows for direct testing of whether structural digital readiness conditions the sustainability effects of economic disasters.

The two-way fixed-effects framework exploits within-country variation over time in disaster exposure while controlling for unobserved heterogeneity across countries. Identification of disaster effects relies on the comparison of sustainability outcomes in disaster years to non-disaster years within the same country, net of global shocks. Two-way fixed effects models are widely used in cross-country panel analyses because they allow researchers to control simultaneously for unobserved country-specific characteristics and common global shocks affecting all countries (Wooldridge, 2010; Baltagi, 2021). By focusing on within-country variation over time, the approach reduces bias arising from time-invariant heterogeneity such as geography, institutional history, or long-run development trajectories. However, fixed-effects models may also have limitations, including potential sensitivity to measurement error and the inability to estimate coefficients on strictly time-invariant variables. In the present study, these limitations are addressed by treating AI preparedness as a structural characteristic and identifying its role through interaction terms with disaster indicators. The fixed-effects framework is therefore well suited for examining how structural digital capacity conditions the sustainability effects of severe macroeconomic shocks across countries.

Potential endogeneity related to AI preparedness is further reduced by treating the index as time-invariant and interacting it with exogenous disaster shocks. This approach follows the logic that, while AI preparedness may shape responses to economic disasters, it is unlikely to be influenced by contemporaneous disaster realisations. This identification strategy therefore allows one to examine how structural digital capacity shapes the timing and magnitude of sustainability losses during periods of severe macroeconomic stress.

Finally, the empirical framework is explicitly grounded in the dynamic-adjustment perspective emphasised by Ćorić (2021). By distinguishing between disaster onset and disaster duration, the model allows for differential short-run and longer-run effects, while interaction terms with AI preparedness capture whether structural digital capacity amplifies or mitigates sustainability losses at different stages of economic disasters. This approach enables a richer interpretation of the results than models focusing solely on average

disaster effects, recognising that resilience is not static but unfolds over time through adjustment processes shaped by structural characteristics. The peak-to-trough identification framework provides several advantages for analysing severe macroeconomic shocks. First, it focuses on large and persistent contractions rather than short-lived fluctuations, thereby isolating economically meaningful disaster episodes (Barro, 2006; Barro & Ursúa, 2008). Second, the method allows transparent identification of both the timing and duration of disasters, which is particularly important when analysing dynamic adjustment processes. At the same time, the approach has some limitations, including sensitivity to the chosen threshold and its reliance on GDP-based measures of economic activity (Ćorić, 2021). Nevertheless, it remains widely used in the disaster literature because it provides a consistent and comparable framework for identifying large macroeconomic shocks across countries. In the context of this paper, the peak-to-trough framework is particularly suitable because it makes it possible to distinguish between disaster onset and disaster duration, thereby capturing both short-run adjustment dynamics and longer-term sustainability effects of severe economic disruptions.

4 Empirical data and analysis

The empirical analysis is based on an unbalanced panel dataset covering a broad sample of countries from the 1990/2000s to the most recent years for which data are available. The analysis starts from the full set of countries worldwide, with the final sample determined by data availability for economic disasters, AI preparedness, and the sustainability indicators. As a result, panel coverage varies across outcome variables. The dataset combines macroeconomic indicators, measures of sustainable development, and a structural indicator of AI preparedness. Its construction closely follows the approach used in Malešević Perović and Ćorić (2024a; 2024b) to ensure comparability with existing findings in the disaster literature.

Macroeconomic data used to identify economic disaster episodes are sourced from the Penn World Table (PWT), version 11.0. Real GDP per capita series from the PWT form the basis for the peak-to-trough disaster identification procedure. As the most recent PWT release does not include observations for 2022-2024, the GDP per capita series are extended using growth rates from the World Bank's World Development Indicators (WDI). This extension preserves the level consistency of the PWT series while allowing coverage of the post-pandemic recovery period, which is particularly relevant for the present study. Economic disaster episodes are identified using this GDP data according to the peak-to-trough methodology developed by Ćorić (2021) and described in Section 3. Two binary economic disasters indicators (dummy variables) are then constructed.

Sustainable development outcomes are captured using three complementary indicators. The adjusted net savings (ANS), obtained from the World Bank, measure the net accumulation of economic, human, and natural capital, providing an intergenerational perspective on sustainability. The Human Development Index (HDI), sourced from the United Nations Development Programme, captures key social dimensions of development, including health,

education, and income. The SDG Index, taken from successive editions of the Sustainable Development Report, provides a composite measure of progress towards the United Nations Sustainable Development Goals. Together, these indicators allow for a multidimensional assessment of sustainable development outcomes, reflecting economic, social, and composite dimensions.

AI preparedness is measured using the Artificial Intelligence Preparedness Index developed by the International Monetary Fund (International Monetary Fund, 2023). The index is designed to capture countries' readiness to adopt and benefit from AI technologies in an economically and socially sustainable manner. It aggregates information across four key pillars: digital infrastructure, human capital and labour market readiness, innovation capacity, and institutional and regulatory frameworks. The AI Preparedness Index is particularly suitable for the present analysis because it captures structural characteristics relevant for long-term development and crisis adjustment. Rather than measuring AI usage or adoption directly, the index reflects the underlying conditions that enable AI to influence economic and social outcomes. As mentioned earlier, a key feature of the index is that it is currently available for a single reference year. Consequently, AI preparedness is treated as a time-invariant country characteristic in the empirical analysis.

The final dataset includes observations for a large and diverse set of countries worldwide, covering different income levels, institutional contexts, and stages of digital development. However, as is common in cross-country analyses, data availability varies across indicators and over time. In particular, missing observations for sustainability indicators limit the effective sample size in some specifications. The empirical analysis uses an unbalanced panel. Adjusted net savings are available for 1990–2021, HDI spans 1990–2023, and the SDG Index covers 2000–2024. Each specification is estimated using the maximum available country–year observations for the respective outcome variable. Using a broad cross-country panel covering several decades allows the analysis to capture a wide range of economic disaster episodes and development trajectories, which is particularly important for studying the long-term sustainability consequences of severe macroeconomic shocks (Barro & Ursúa, 2008; Malešević Perović & Ćorić, 2024a).

5 Results and discussion

Table 1 presents the baseline estimation results for the relationship between economic disasters, AI preparedness, and sustainable development outcomes. Columns (1)–(3) report results using the disaster duration indicator (ED_duration), while columns (4)–(6) focus on disaster onset (ED_onset). In specifications (1) and (2), the results confirm the hypothesis that economic disasters are associated with adverse sustainability outcomes. For adjusted net savings (ANS), disaster duration is associated with a statistically significant and economically meaningful decline. This indicates that prolonged economic disasters reduce net capital accumulation, reflecting pressures on fiscal balances, reduced investment, and potential depletion of natural and human capital. The magnitude of the estimated coefficient is consistent with previous findings reported by Malešević Perović and Ćorić (2024a), confirming that

economic disasters undermine sustainability. Similarly, disaster duration is associated with a statistically significant decline in the Human Development Index (HDI). This reflects the combined effects of labour market disruptions, reduced access to education and healthcare, and income losses during periods of severe economic stress. By contrast, the coefficient on disaster duration for the SDG Index is not statistically significant. This likely reflects the composite and relatively slow-moving nature of the SDG Index, which aggregates outcomes across multiple domains and may not fully capture short-term economic and social stress.

Table 1: Results

Dependent variable: SD	(1)	(2)	(3)	(4)	(5)	(6)
	ANS	HDI	SDG Index	ANS	HDI	SDG Index
ED_duration	-4.1604***	-0.0068***	0.0642			
	(0.9199)	(0.0021)	(0.1665)			
ED_duration*aipi_z	-0.7988	0.0009	0.1908			
	(0.9427)	(0.0032)	(0.2409)			
ED_onset				0.6837	0.0005	0.0903
				(0.9074)	(0.0020)	(0.1360)
ED_onset*aipi_z				0.2206	-0.0066***	-0.0774
				(1.0393)	(0.0024)	(0.1626)
Observations	3483	4604	3550	3483	4604	3550

Note: Standard errors in parentheses; Country and year fixed effects included; Standard errors clustered at the country level; * p < 0.10, ** p < 0.05, *** p < 0.01; The sample period varies across specifications due to differences in data availability. ANS covers 1990–2021, HDI 1990–2023, and the SDG Index 2000–2024. All models are estimated on unbalanced panels.
Source: Author

When considering prolonged economic disasters, the interaction terms between AI preparedness and disaster duration are statistically insignificant across all three sustainability indicators. This indicates that higher AI preparedness does not significantly mitigate or amplify sustainability losses associated with extended periods of severe economic stress. Two implications follow from this finding. First, structural digital readiness alone appears insufficient to offset the adverse effects of prolonged disasters. Even in digitally prepared economies, sustained economic contractions continue to erode fiscal capacity, disrupt labour markets, and weaken social outcomes. Second, the

absence of a significant interaction during disaster duration suggests that any potential benefits of AI preparedness may require time to materialise and may be contingent on recovery dynamics rather than contemporaneous crisis conditions. This interpretation is consistent with the disaster-adjustment framework, which emphasises that structural characteristics primarily shape longer-term recovery paths rather than immediate crisis outcomes (Ćorić, 2021).

A more nuanced pattern emerges when focusing on disaster onset. For adjusted net savings and the SDG Index, the interaction terms between AI preparedness and disaster onset are not statistically significant. In contrast, in terms of the Human Development Index, the interaction between AI preparedness and disaster onset is negative and statistically significant. This result indicates that countries with higher AI preparedness experience a sharper short-run decline in human development at the onset of economic disasters. This finding is central to the paper's contribution and provides empirical support for a dynamic-adjustment interpretation of the results.

From a theoretical perspective, this pattern suggests that digitally prepared economies may undergo faster and more intensive adjustment processes when confronted with severe shocks. Rapid restructuring, automation, and labour reallocation – facilitated by higher AI readiness – may initially amplify social stress, particularly through labour-market disruptions and reduced access to social services. These processes can temporarily worsen human development outcomes even when they potentially lay the groundwork for longer-term efficiency gains.

6 Conclusions

Existing research has documented the sustainability consequences of economic disasters and the growing importance of artificial intelligence for economic development, but little empirical evidence exists on how AI preparedness may influence the sustainability effects of severe macroeconomic shocks. This paper examined whether countries' preparedness for artificial intelligence influences the sustainability effects of economic disasters. Building on the disaster-adjustment framework developed in the recent disaster literature, the analysis introduced AI preparedness as a new structural dimension in the study of economic disasters and sustainable development. By combining a peak-to-trough identification of economic disasters with multiple sustainability indicators, the paper provides new evidence on how digital readiness shapes the timing and magnitude of sustainability losses during severe macroeconomic shocks.

The empirical results confirm that economic disasters are associated with significant short-term losses in key dimensions of sustainable development. These findings provide empirical support for H1, which predicted that economic disasters are associated with deteriorations in sustainable development outcomes. Contrary to this, H2, which expected that AI preparedness would moderate the sustainability effects of economic disasters, receives only limited support. While AI preparedness does not significantly alter sustainability

outcomes during prolonged disaster periods, it is associated with sharper short-run declines in human development at the onset of economic disasters. This suggests that AI preparedness primarily influences the timing rather than the overall magnitude of sustainability effects. Prolonged disaster periods are linked to substantial declines in adjusted net savings and human development, reflecting pressures on fiscal capacity, reduced investment, and adverse social outcomes. These findings reinforce the existing evidence that economic disasters undermine the foundations of sustainable development and may generate long-lasting scarring effects that extend beyond the immediate crisis period.

The central contribution of the paper is the analysis of interaction effects between AI preparedness and economic disasters. Contrary to a simple resilience narrative, the results do not suggest that AI preparedness systematically mitigates the adverse sustainability effects of economic disasters. Instead, a more nuanced pattern emerges. While AI preparedness does not significantly alter sustainability outcomes during prolonged disaster periods, it is associated with sharper short-term declines in human development at the onset of economic disasters. This finding provides empirical support for a dynamic-adjustment interpretation of disaster effects.

From a conceptual perspective, the results suggest that structurally prepared economies – those with advanced digital infrastructure, skilled labour forces, and stronger institutions – may be able to adjust more rapidly when confronted with large shocks. However, rapid adjustment can intensify short-term social costs, particularly through labour-market disruptions and reduced access to social services. In this sense, AI preparedness appears to shape the timing rather than the direction of sustainability effects, amplifying short-term welfare losses while potentially facilitating longer-term adaptation. Importantly, these findings do not imply that AI preparedness is detrimental to sustainable development. Rather, they highlight that technological readiness alone does not guarantee social resilience. Without complementary labour-market policies, social protection, and redistribution mechanisms, rapid technological and structural adjustment may exacerbate short-term welfare losses during crises.

Several limitations of the analysis should be acknowledged. The empirical model is intentionally parsimonious, focusing on the interaction between economic disasters and AI preparedness in order to preserve interpretability and comparability with the existing disaster literature. While this approach has clear advantages, it necessarily abstracts from other potentially relevant factors—such as GDP per capita, natural resource rents, or broader crisis indicators —which could be incorporated in future research. In addition, AI preparedness is measured using a single composite index available for one reference year. Although the IMF AI Preparedness Index captures structural readiness for AI adoption, it does not allow for an analysis of changes in AI preparedness over time. Consequently, the results should be interpreted as a reflection of how pre-existing digital capacity conditions the effects of economic disasters, rather than how the dynamic evolution of AI adoption shapes sustainability outcomes. Future work could therefore benefit from employing alternative or complementary AI-related indicators as such data

become available. Finally, the use of composite sustainability measures—particularly the SDG Index—may mask short-run dynamics within specific development dimensions. Nevertheless, this concern is partly mitigated by the use of multiple sustainability indicators in the empirical analysis.

Despite these limitations, this paper represents a first step in examining the role of AI preparedness in shaping the sustainability consequences of economic disasters. This is a paper related to the topic with significant lack of systematic and comprehensive research. Insights from this paper complement existing work in the disaster literature and underscore the need to integrate digital transformation into broader discussions of economic stability and sustainable development.

Future research could extend this analysis by incorporating additional macroeconomic control variables, exploring alternative or time-varying indicators of AI preparedness, and examining specific dimensions of sustainable development in greater detail.

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Use of Artificial Intelligence (AI) or AI-based Tools: *During the preparation of this manuscript, the author used ChatGPT to assist with language editing, improving clarity of expression, and stylistic revisions of the text. After using this tool, the author reviewed and edited the content as necessary and takes full responsibility for the content of the published article.*

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Artificial Intelligence in Finance: Opportunities, Risks and Applications

Preliminary communication

Dario Silić[1], Mario Silić[2], Ivana Silić[3]

ABSTRACT

Artificial intelligence (AI) has become a central driver of digital transformation within the financial sector, influencing decision-making, productivity, and risk allocation across banking, capital markets, asset management, and financial supervision. The increasing availability of large-scale financial data, combined with advances in machine learning and computational power, has enabled financial institutions to deploy AI systems for trading, portfolio optimization, risk management, fraud detection, and regulatory compliance. At the same time, the growing reliance on algorithmic decision-making introduces new challenges related to model risk, explainability, bias, and systemic stability. This paper provides a comprehensive academic analysis of AI applications in finance, focusing on opportunities and risks of adopting AI within the fields of data and machine learning, AI in trading, portfolio management and robo-advisory services, AI-driven risk management, fraud detection, and compliance. This research paper employs qualitative documentary analysis of publicly available industry and regulatory materials. By synthesizing academic research and policy-oriented literature, the paper contributes to the understanding of how AI reshapes financial intermediation while highlighting the conditions under which its deployment can support sustainable and responsible financial innovation.

Keywords: *Artificial intelligence, Machine learning, Financial markets,*

1 *Professor, University of Applied Sciences in Security and Safety ,Veslačka 2a, 10000 Zagreb, Croatia, Scientific affiliation: Financial management,Corporate Finance, Financial modeling. Phone_Number: +3859168509109. E-mail: dario@ssbm.ch*

2 *Professor, University of Applied Sciences in Security and Safety, Veslačka 2a, 10000 Zagreb, Croatia, Scientific affiliation: IT, Management. Phone_Number: +385914603892. E-mail: mario@ssbm.ch*

3 *Lecturer, University of Applied Sciences in Security and Safety, Veslačka 2a, 10000 Zagreb, Croatia, Scientific affiliation: Financial management,Corporate Finance, Financial modeling. Phone_Number: +385911408198. E-mail: ivana.silic@ssbm.ch*

Algorithmic trading, Robo-advisors, Risk management, Financial regulation

***JEL classification**: G10, G11, G17, G21, G28*

1 Introduction

The financial world is undergoing a technological revolution, and at the heart of it lies Artificial Intelligence. The financial sector has historically been at the forefront of adopting quantitative methods and advanced information technologies. From early portfolio theory and econometric modeling to the automation of trading and payment systems, finance has continuously evolved alongside technological progress. In recent years, artificial intelligence (AI) has emerged as a general-purpose technology with far-reaching implications for financial intermediation, market efficiency, and financial stability. AI systems, particularly those based on machine learning (ML), differ from traditional rule-based algorithms in that they learn complex, non-linear patterns from large datasets and adapt continuously to new information.

This paper offers a comprehensive exploration of opportunities, risks and applications of AI in finance and how AI is progressively transforming traditional finance into a data-driven, intelligent ecosystem. It is important to understand the fundamentals of AI and machine learning, before diving into the immense opportunities AI creates -from automating trades to predicting market shifts - and the critical risks it brings, such as algorithmic bias, data misuse, and regulatory challenges. A solid foundation in data science principles and machine learning techniques will equip one to grasp the inner workings of AI models, especially in financial contexts.

This study is based on the qualitative documentary analysis of publicly available industry and regulatory materials. Through examples about applications in finance, we will explore how AI is used in algorithmic trading, robo-advisory platforms, portfolio optimization, and risk management, helping firms make faster, smarter, and more personalized decisions. The paper also examines the vital role of AI in fraud detection and regulatory compliance, where real-time anomaly detection and behavioral modeling help institutions fight increasingly sophisticated financial crimes. Special attention is given to explainability, ethics, and the evolving regulatory environment, ensuring everyone understands both the power and responsibility that come with AI integration.

The growing relevance of AI in finance is driven by several structural developments. First, financial markets and institutions generate massive volumes of heterogeneous data, including high-frequency market data, transactional records, textual disclosures, and alternative data sources. Second, intensified competition and margin pressure motivate financial institutions to seek productivity gains through automation and improved predictive accuracy. Third, increasing regulatory complexity has created demand for advanced analytical tools capable of monitoring risk exposures and compliance in real time. According to the BCBS (2018), AI has the potential to enhance risk sensitivity and operational efficiency, but also to introduce new

forms of model risk and systemic interdependence.

Several surveys have examined artificial intelligence and machine learning applications in finance, often focusing on specific domains such as trading strategies (López de Prado, 2018), credit risk modeling (Fuster et al., 2022), or portfolio construction (Heaton et al., 2017). However, much of the existing literature remains fragmented across functional areas and emphasizes technical performance without systematically integrating governance, ethical, and systemic considerations. More recent policy-oriented work highlights the growing importance of explainability, accountability, and model risk management but is often disconnected from empirical finance research (Maheshwari et al., 2025; Danielsson et al., 2017). This paper contributes to the literature by providing an integrated review that links AI applications in finance with their institutional, regulatory, and systemic implications.

From an academic perspective, AI in finance represents a convergence of financial economics, data science, and regulatory studies. While early research focused on the technical performance of machine learning models, recent literature increasingly emphasizes governance, transparency, and ethical considerations. This paper adopts an integrated approach by combining insights from financial economics, empirical finance, and regulatory policy. The research objective of this paper is to systematically review and analyze the existing literature on the applications of artificial intelligence in finance in order to provide a comprehensive understanding of the development, current state and future trends in the application of AI in finance. The review seeks to identify key themes, risks, challenges, and opportunities across various domains within the financial industry, including risk management, fraud detection, customer service and investment strategies. In addition, the research aims to uncover gaps in the literature and contribute insights that can inform future research directions and practical implementations in the rapidly evolving landscape of AI in finance.

This paper contributes to the literature by providing an integrated, domain-spanning review of AI applications in finance that explicitly links technical performance, economic implications, and regulatory governance. Unlike prior surveys focused on individual applications, it synthesizes opportunities and risks across trading, portfolio management, risk modeling, and compliance within a unified analytical framework.

The objective of this paper is to systematically review and analyze the literature on AI applications in finance in order to summarize the development, current state, and emerging trends, and to identify key opportunities and risks across major financial domains.

The paper addresses three research questions:

RQ1: What are the dominant application areas of AI in contemporary financial services and markets?
RQ2: What opportunities (efficiency, accuracy, scalability) and risks (model risk, bias, opacity, systemic effects) arise from AI adoption?
RQ3: What governance and regulatory conditions enable responsible AI deployment in finance?

Section 2 reviews opportunities and risks of AI adoption in finance. Section 3 presents the methodology. Section 4 outlines data and ML foundations. Section 5 analyzes AI in trading. Section 6 discusses portfolio management and robo-advisory services. Section 7 covers risk management, fraud detection, and compliance. Section 8 provides discussion and implications. Section 9 concludes and outlines directions for future research.

2 Artificial intelligence in finance

AI is a broad term describing computational systems that perform tasks requiring human-like intelligence, including prediction, classification, and decision support. ML is a subset of AI that learns patterns from data. Deep learning (DL) is a subset of ML using multi-layer neural networks, often effective with high-dimensional inputs such as text, images, and complex time series. Natural language processing (NLP), an area of AI focused on language understanding and generation, is increasingly applied in finance to extract information from earnings calls, news, regulatory filings, and other unstructured sources (Hilpisch, 2020; López de Prado, 2018; Tetlock, 2007).

Artificial intelligence has become an increasingly prominent subject of academic inquiry within finance, reflecting its growing role in financial intermediation, market functioning, and regulatory oversight. A rapidly expanding literature examines the application of machine learning and related techniques across trading, asset management, credit markets, and financial supervision. This section provides a structured review of that literature, focusing on two interrelated dimensions: the opportunities created by AI adoption and the risks and challenges associated with algorithmic decision-making in financial systems.

In the financial context, AI primarily refers to the application of machine learning methods for prediction, classification, optimization, and decision support. Unlike traditional econometric models, machine learning emphasizes flexible, data-driven learning of complex, often non-linear relationships and is particularly well suited to high-dimensional environments (Mullainathan and Spiess, 2017; Athey, 2018). Deep learning methods further extend these capabilities through hierarchical feature learning, while natural language processing (NLP) enables the extraction of informational signals from unstructured textual data such as news, earnings call transcripts, and regulatory filings (Tetlock, 2007; López de Prado, 2018; Hilpisch, 2020).

2.1 Opportunities

A substantial body of research highlights the potential of AI to enhance efficiency, scalability, and predictive accuracy across financial services. One prominent opportunity lies in process automation. Machine learning systems are increasingly deployed to automate credit assessment, transaction monitoring, trade execution, reconciliation, and regulatory reporting, leading to reductions in operational costs and processing times (Brynjolfsson & McAfee, 2017; BCBS, 2018).

In credit markets, empirical evidence suggests that machine learning models can outperform traditional scorecard-based approaches in predicting default risk. Fuster et al. (2022) demonstrate that ML-based credit models improve predictive accuracy relative to conventional methods, while also altering the distribution of credit access across borrowers. Related studies emphasize that the economic value of these models depends on how predictions are integrated into lending decisions, pricing, and risk management frameworks rather than on accuracy metrics alone (Mullainathan & Spiess, 2017; Berg et al., 2020).

In capital markets, AI has been widely adopted in algorithmic trading and market microstructure analysis. Gu, Kelly, and Xiu (2020) show that machine learning methods outperform traditional factor models in return prediction in high-dimensional settings. Feng et al. (2024) and López de Prado (2018) provide further evidence that ML techniques can extract economically meaningful signals from large financial datasets. These findings are consistent with the research showing that AI systems can process market information at speeds and scales beyond human capabilities, potentially contributing to faster price discovery and improved liquidity (Biais et al., 2015; Kirilenko et al., 2017).

Asset management represents another important application domain. Machine learning-based portfolio optimization techniques relax the assumptions of linearity and normality underlying traditional mean-variance frameworks and allow for time-varying correlations, regime shifts, and non-linear payoffs. Heaton, Polson, and Witte (2017) provide early evidence that deep learning approaches can improve portfolio performance under certain conditions, while Ang (2014) and Gu et al. (2020) emphasize the importance of systematic integration of predictive signals into portfolio construction and risk management.

In retail finance, AI has enabled the rapid growth of robo-advisory platforms that provide automated investment advice based on client characteristics and algorithmic portfolio construction rules. Empirical studies find that robo-advisors can improve diversification, reduce fees, and mitigate certain behavioral biases, although their effectiveness depends on investor engagement and understanding (D'Acunto et al., 2019; Jung et al., 2018; Linnainmaa et al., 2021).

AI also plays a crucial role in fraud detection and anti-money laundering (AML). Machine learning-based anomaly detection systems adapt to evolving fraud patterns and reduce false positives relative to rule-based systems, improving both compliance effectiveness and customer experience (Bolton & Hand, 2002; Dal Pozzolo et al., 2015; BCBS, 2018). These applications are particularly valuable in high-volume transaction environments where manual monitoring is infeasible.

Beyond operational efficiency, recent research emphasizes that the economic value of AI models depends not only on predictive accuracy but also on their integration into decision-making processes and cost structures. Gu, Kelly, and Xiu (2020) demonstrate that machine learning methods can outperform traditional factor models in predicting asset returns, although gains are sensitive to transaction costs and model stability. Similarly, Brynjolfsson,

Rock, and Syverson (2021) argue that productivity gains from AI are realized unevenly due to complementary investments in organizational capital and data infrastructure.

In fraud detection and anti-money laundering (AML), machine learning models often outperform traditional rule-based systems by identifying evolving patterns of suspicious behavior, reducing false positives. This improves both risk management effectiveness and customer experience (Bolton & Hand, 2002). Empirical studies also show that ML-based credit models can improve default prediction relative to traditional statistical approaches and may expand access to credit under certain conditions (Fuster et al., 2022).

In capital markets, AI contributes to faster price discovery and improved liquidity provision. Algorithmic trading systems analyze market microstructure data and execute trades within milliseconds, potentially reducing transaction costs and bid-ask spreads. In asset management, AI-based portfolio optimization methods allow for the incorporation of non-linear relationships, time-varying correlations, and alternative data sources, which may improve risk-adjusted returns compared to static models (Heaton et al., 2017).

Overall, AI enables financial institutions to process information at a scale and speed that exceeds human capabilities, supporting real-time decision-making in environments characterized by high complexity and uncertainty.

2.2 Risks

AI adoption introduces material risks at model, operational, legal, ethical, and systemic levels. A widely cited challenge is the opacity (“black-box” behavior) in complex models such as deep neural networks, which can hinder accountability and explainability in regulated decisions (Lipton, 2018). Bias and fairness risks arise when models trained on historical data reproduce discriminatory patterns, including those in lending contexts (Fuster et al., 2022). At a systemic level, correlated model architectures, shared datasets, and similar optimization objectives may increase herding behavior and procyclicality, amplifying stress events (Borio, 2019). These concerns motivate stronger governance, stress testing, monitoring, and regulatory oversight.

From a financial economics perspective, AI-related risks can be categorized into model risk, data risk, operational risk, conduct risk, and systemic risk. Model risk arises from overfitting, instability, and regime dependence, particularly in non-stationary financial environments (Bailey et al., 2014). Data risk reflects issues related to data quality, representativeness, and privacy. Operational risks include system failures, cyber vulnerabilities, and vendor concentration. Conduct and legal risks emerge when AI systems produce biased or opaque decisions in regulated activities such as lending or investment advice. Finally, systemic risk may arise from correlated model behavior across institutions, amplifying market volatility during stress events (Borio, 2019; Danielsson et al., 2017).

A PwC study revealed that 40% of millennials already say they would prefer financial advice from AI over a human banker (PwC, 2022). Artificial Intelligence (AI) is the broad concept - machines performing tasks requiring

human-like intelligence. Machine Learning (ML) is a subset - algorithms that learn patterns from data. Deep Learning (DL) is a further subset using multi-layered neural networks, inspired by the human brain. And then we have Natural Language Processing (NLP), which lets machines understand and process human language. In finance, NLP is critical - for example, hedge funds use it to analyze thousands of earnings calls and news headlines in real time to make investment decisions (Hilpisch, 2020; Lopez de Prado, 2018).

AI brings opportunities but also risks. For instance, flash crashes in 2010 and 2015 were partly caused by algorithms reacting to each other faster than humans could intervene. Regulators are worried that AI could make the next financial crisis worse by amplifying mistakes at speed (PwC, 2022; Deloitte, 2023).

On the opportunity side, AI significantly improves efficiency and speed by automating processes such as credit scoring, trading execution, and compliance checks.

Financial institutions can process vast amounts of data in real time, leading to lower operational costs and faster response times. AI is also widely used in fraud detection, where machine learning models identify unusual transaction patterns more accurately than traditional rule-based systems. This improves risk management while reducing false positives, which directly enhances customer experience. Overall, these capabilities allow banks and financial firms to scale services and to compete more effectively.

Machine learning models can process information at speeds and levels of complexity that exceed human capabilities, enabling real-time analysis of market movements, creditworthiness, and operational risks. Empirical evidence suggests that AI-based credit scoring models can outperform traditional statistical approaches in predicting default risk while expanding access to credit (Fuster et al., 2022).

Despite these benefits, AI adoption also introduces significant risks. One of the most widely discussed challenges is model opacity, often referred to as the “black box” problem. Complex models such as deep neural networks may achieve superior predictive performance but lack interpretability, making it difficult to explain decisions to regulators, clients, and internal stakeholders (Lipton, 2018). This issue is particularly problematic in regulated areas such as credit decisions and investment advice. Algorithmic bias represents another critical risk. AI systems trained on historical data may reproduce or amplify existing social and economic inequalities, especially when sensitive attributes are implicitly encoded in input variables. Empirical studies have documented discriminatory outcomes in automated lending and hiring systems, raising concerns about fairness and legal compliance (Fuster et al., 2022). At the systemic level, widespread reliance on similar data sources and AI models may increase market correlation and pro-cyclicality. During periods of stress, synchronized model behavior can amplify price movements and liquidity shortages, potentially threatening financial stability (Borio, 2019). These risks underscore the importance of robust governance frameworks, stress testing, and regulatory oversight.

2.3 Governance and regulatory perspectives

In response to these risks, a growing policy-oriented literature emphasizes the importance of governance, explainability, and regulatory oversight of AI systems in finance. The Bank for International Settlements (2020, 2021) highlights the need for robust model governance frameworks covering data management, validation, documentation, and human oversight throughout the AI lifecycle. Similar themes emerge in supervisory guidance from central banks and financial regulators, which stress accountability and auditability of algorithmic decisions.

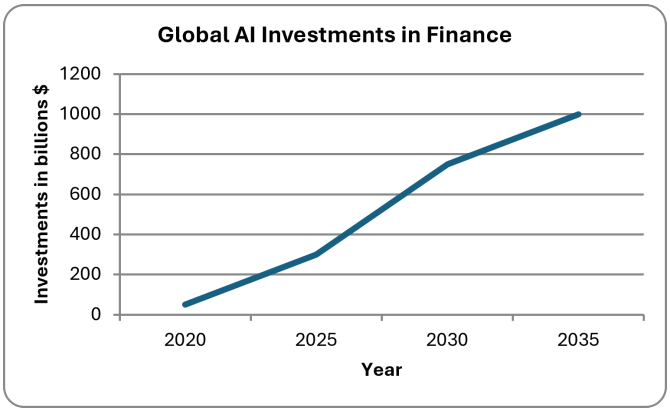
Emerging regulatory frameworks reflect these concerns. The European Union's Artificial Intelligence Act classifies many financial AI applications as high-risk and imposes requirements related to transparency, robustness, and fairness (European Commission, 2024). In the United States, regulators have expressed concerns about the potential of AI to mislead investors or exacerbate systemic risk, prompting proposals for enhanced disclosure and oversight of algorithmic decision-making (SEC, 2023).

Overall, the literature converges on the view that AI in finance should be understood not merely as a technical innovation but as an institutional transformation that reshapes risk allocation, governance structures, and regulatory responsibilities. Effective deployment therefore requires aligning technological capabilities with financial stability objectives and societal expectations.

The key conclusion is that AI in finance is not just a technical tool, but a strategic capability that requires strong governance, ethical oversight, and risk management.

Chart 1 illustrates the rapid growth of global investment in artificial intelligence within the financial sector, based on aggregated estimates from consulting reports and institutional surveys. While projections vary significantly across sources, the common trend indicates sustained growth driven by increased adoption in trading, risk management, and compliance. These figures should be interpreted as indicative rather than precise forecasts, reflecting uncertainty regarding technological diffusion, regulation, and macroeconomic conditions. For example: JPMorgan spends $12 billion annually on technology, much of it on AI (McKinsey Global Institute, 2023). A logical question can be asked: Should smaller banks even try to compete, or just adopt off-the-shelf AI solutions?

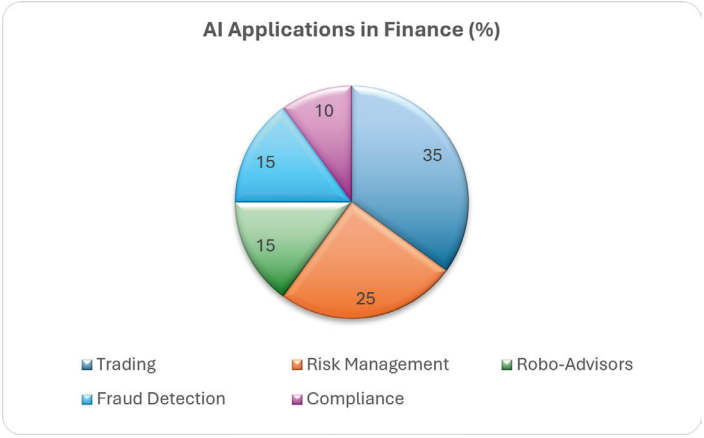
Chart 1: Global AI investments in finance from 2020 to 2035



Source: Authors based on PwC (2017), McKinsey Global Institute (2023), and Stanford AI Index (2024)

Chart 2 presents an illustrative allocation of AI applications across major functional areas in finance, based on synthesis of industry surveys and institutional reports. Trading and market microstructure applications account for a substantial share of AI deployment, reflecting the importance of speed and data processing capabilities in capital markets. Risk management, fraud detection, and robo-advisory services represent significant but heterogeneous application domains, while compliance-related uses are growing rapidly due to increasing regulatory requirements.

Chart 2: AI applications in finance



Source: Author's aggregation based on PwC (2017), BCBS (2018), McKinsey Global Institute (2023; 2025), and Stanford AI Index (2024)

We can see that trading dominates with 35%, and this is where AI is most heavily used today. Hedge funds, quant teams, and algo-traders like Renaissance Technologies or Citadel deploy ML models to forecast price patterns and execute trades in milliseconds. Risk management is at 25%. AI is used in banks to build predictive models that alert for credit defaults, market crashes, or liquidity crises. A good example is JPMorgan which uses machine learning for stress testing large portfolios under simulated economic shocks. The robo-advisors and fraud detection are at 15% each. Platforms like Wealthfront and Betterment automate personalized investing based on financial goals, timeline, and risk tolerance - all powered by AI. Visa and Mastercard use real-time anomaly detection algorithms that scan millions of transactions in less than 300 milliseconds. Machines beat humans on speed and volume, hands down.

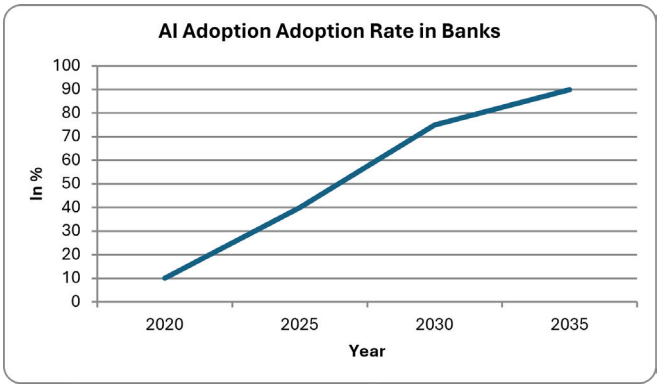
Finally, compliance is at 10%. RegTech firms like Ayasdi use AI to help financial institutions automate KYC (Know Your Customer) and AML (Anti-Money Laundering) compliance.

While it is a smaller slice of the pie, it is growing fast due to tighter global regulations. “Global investment in AI for trading alone is projected to exceed $300 billion by 2030 (McKinsey, 2023). So, it makes sense trading dominates this chart.” In US equity markets, 60% of trades are now algorithmic. Many of them use ML models. In 2024, over 60% of hedge funds used AI in trading strategies (Preqin, 2024).

Bank of America uses AI to monitor over 50 million transactions per day for AML and fraud. The BlackRock’s Aladdin platform uses AI to assess portfolio risk across trillions in AUM. Wealthfront and Betterment together manage over $70 billion using AI-powered portfolio allocation, rebalancing, and goal-based investing (PwC, 2022; McKinsey Global Institute, 2023).

Chart 3 depicts reported and projected adoption rates of AI systems in banking, based on survey evidence from regulatory and consulting sources.

Chart 3: AI Adoption rate in banks from 2020 to 2035

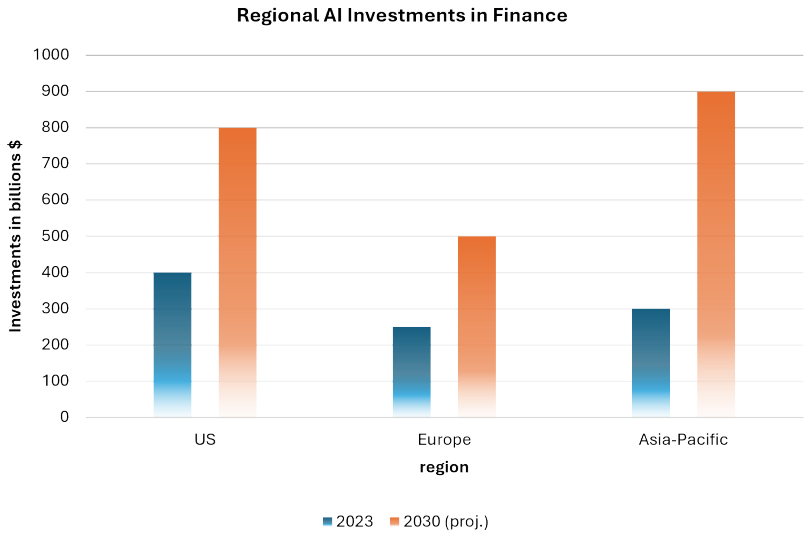


Source: Author’s aggregation based on (BCBS, 2018; McKinsey Global Institute, 2025)

While adoption has increased substantially over the past decade, high reported adoption does not necessarily imply effective or value-creating use. Prior research highlight that AI performance depends critically on data governance, model validation, and organizational integration, suggesting that adoption alone is not a sufficient indicator of improved outcomes (Brynjolfsson et al., 2021). Already, 56% of banks report at least one AI system in place (Deloitte, 2022). By 2030, regulators expect AI to be standard for compliance and risk checks. Does higher adoption always mean better performance? As history has shown, this is not always the case and it will be discussed later on in the text.

Chart 4 highlights regional differences in AI investment within the financial sector. The projected growth in the Asia-Pacific region reflects large-scale public and private investment in fintech and AI infrastructure, particularly in China. Differences across regions may also reflect regulatory environments, data availability, and institutional structures, which influence both the pace and direction of AI adoption. In 2023, the US led regional markets with $400B, compared to $300B for Asia-Pacific and $250B for Europe. However, fueled by China's massive investments in fintech and AI, the Asia-Pacific region is projected to surpass $900B and overtake the US by 2030, sparking concerns that Europe may fall behind permanently.

Chart 4: Regional AI investments in finance in 2023 and projection for 2030



Source: Author's illustration based on empirical findings from Fuster et al. (2022), BCBS (2018), and McKinsey Global Institute (2023; 2025)

AI is already reshaping finance - from trading to compliance. Opportunities are huge but so are the risks.

3 Methodology

This study employs a qualitative research design combining a structured literature review with an industry-oriented qualitative investigation of documented AI adoption practices in financial services. The research is exploratory and analytical in nature, aiming to map dominant application domains of AI in finance and to identify associated opportunities, risks, and governance requirements.

The study follows an interpretive approach, focusing on how AI systems are described, implemented, and governed within financial institutions and regulatory frameworks rather than on proprietary model performance evaluation.

3.1 Literature review strategy

The first phase consisted of an extensive literature review focusing on peer-reviewed academic research and policy-oriented publications. Sources include journals in finance, computational economics, risk management, and financial regulation, as well as institutional reports from entities such as BIS, IMF, and regulatory bodies. The literature was selected based on relevance to key topics including algorithmic trading, portfolio optimization, robo-advisory services, risk modeling, fraud detection, and AI governance frameworks.

A structured search strategy was used to identify peer-reviewed research and policy-oriented publications relevant to: (a) AI/ML foundations for finance, (b) trading and market microstructure, (c) portfolio management and robo-advice, (d) risk forecasting and stress testing, and (e) fraud/AML and regulatory compliance. Priority was given to high-quality sources such as peer-reviewed journals and institutional publications (e.g., BIS, IMF), supplemented by industry research for operational examples. Inclusion criteria favored works that: (1) propose or evaluate AI methods in financial contexts, (2) report empirical results, or (3) provide policy and governance frameworks. The exclusion criteria removed sources lacking relevance to finance or containing insufficient methodological transparency.

3.2 Industry-oriented qualitative investigation

The second phase of the research involved an industry-oriented qualitative investigation based on structured analysis of publicly available case studies, institutional disclosures, regulatory consultations, and practitioner reports. This component is best characterized as a qualitative interpretive synthesis of documented industry practices rather than a classical ethnography based on participant observation. The purpose of this investigation is to contextualize academic findings by examining how AI systems are operationalized within real-world financial workflows, including trading platforms, credit assessment tools, risk engines, and compliance systems

3.3 Data collection and materials

This paper relies primarily on secondary qualitative and empirical materials, including:

- peer-reviewed studies on AI performance, forecasting, credit risk, and portfolio construction,
- regulatory and supervisory publications (e.g., BIS reports, EU AI Act documents, SEC proposals),
- industry evidence from major financial institutions and technology providers (e.g., JPMorgan, BlackRock, fintech platforms),
- empirical findings reported in prior quantitative studies referenced throughout the paper.

The included charts represent visual syntheses of reported empirical findings and aggregated estimates from referenced sources, intended to illustrate trends and adoption patterns rather than to provide original econometric estimations.

3.4 Data analysis approach

Findings were analyzed using thematic synthesis. Identified evidence was categorized into five dominant application domains:

1. AI in trading and market microstructure
2. AI in portfolio management and robo-advisory systems
3. AI-driven risk management and forecasting models
4. AI in fraud detection and AML monitoring
5. AI governance, explainability, and regulatory compliance.

The study further classifies AI-related risks into model risk, operational risk, legal/compliance risk, ethical risk (bias/fairness), and systemic risk.

3.5 Reliability, validity and limitations

The study improves reliability through triangulation between academic literature and institutional evidence. However, several limitations remain. First, the study does not rely on proprietary bank datasets or internal model performance metrics. Second, the industry evidence is partially based on publicly available documentation, which may reflect strategic or marketing narratives. Third, AI performance depends heavily on institutional context, data quality, and regulatory environments, which may limit generalization of findings across jurisdictions.

3.6 Ethical considerations

Given the focus on AI systems that influence lending, investment, and compliance decisions, ethical concerns such as transparency, accountability, bias, and privacy are central to the analysis. The paper highlights the importance of responsible AI principles, including explainability, governance oversight, auditability, and compliance with emerging regulatory requirements.

4 Data and machine learning foundations

The effectiveness of artificial intelligence systems in finance critically depends on the availability, quality, and structure of data. Financial data is heterogeneous and can be broadly classified into four categories: market data, fundamental data, textual data, and alternative data. Each category presents distinct challenges and opportunities for machine learning applications.

Market data include asset prices, returns, trading volumes, and order book information. These data are typically high-frequency, noisy, and non-stationary, reflecting rapid information flows and strategic interactions among market participants. Fundamental data consists of accounting statements, balance sheets, income statements, and financial ratios, which are lower in frequency but provide insights into firm value, profitability, and creditworthiness. Textual data, such as news articles, earnings call transcripts, analyst reports, and regulatory filings, have gained increasing importance with advances in natural language processing (NLP). Alternative data sources, including satellite imagery, transaction metadata, web traffic, and geolocation data-further expand the informational set available to financial institutions.

Machine learning techniques applied in finance span supervised learning, unsupervised learning, and reinforcement learning. Supervised learning methods, including linear and logistic regression, random forests, gradient boosting machines, and neural networks, are widely used for prediction and classification tasks such as credit scoring, fraud detection, and return forecasting. Unsupervised learning techniques, such as clustering and anomaly detection, are employed to identify latent structures in data and to detect unusual patterns without labeled outcomes. Reinforcement learning approaches, which learn optimal actions through interaction with an environment, have been explored in trading, execution optimization, and dynamic portfolio allocation.

Financial time series pose particular challenges for machine learning due to non-stationarity, regime shifts, heavy tails, and feedback effects between model outputs and market behavior (Tsay, 2010). Models trained on historical data may perform poorly when underlying market conditions change, highlighting the importance of robust validation and continuous monitoring.

The empirical finance literature emphasizes the risks of overfitting, data leakage, and selection bias in machine learning applications. Bailey et al. (2014) demonstrate that a substantial proportion of reported trading strategies suffer from back test overfitting, leading to inflated in-sample performance and disappointing out-of-sample results. As a result, responsible AI deployment

in finance requires rigorous cross-validation, out-of-sample testing, realistic transaction cost assumptions, and ongoing performance evaluation under live conditions.

5 Artificial intelligence in trading and market

Artificial intelligence has become a central component of modern trading strategies, particularly in algorithmic and high-frequency trading. Machine learning models are used to generate predictive signals, optimize execution strategies, manage intraday risk, and adapt trading behavior to evolving market conditions.

Supervised learning models are commonly applied to short-horizon return prediction, volatility forecasting, and liquidity estimation. Reinforcement learning approaches have been used to design adaptive trading and market-making strategies that optimize execution quality under uncertain and dynamic market environments (Moody and Saffell, 2001). These methods allow algorithms to balance trade-offs between market impact, execution speed, and price risk.

Natural language processing plays an increasingly important role in trading by extracting informational signals from unstructured textual data. Seminal work by Tetlock (2007) demonstrates that media sentiment contains information relevant for stock returns, while subsequent research show that combining sentiment measures with traditional market variables can improve short-term forecasting accuracy. Advances in deep learning have further enhanced the ability to process earnings call transcripts, news feeds, and social media data in near real time.

The economic rationale for AI-driven trading is rooted in speed, scalability, and information processing capacity. Financial markets generate vast volumes of data that exceed human analytical capabilities, particularly at high frequencies. AI systems enable rapid analysis and execution, potentially contributing to faster price discovery and reduced transaction costs. However, the increasing autonomy and speed of trading algorithms also raise concerns regarding market stability.

Historical episodes of extreme intraday volatility, such as the 2010 Flash Crash, illustrate how automated trading systems can interact in complex and unforeseen ways. While regulatory safeguards such as circuit breakers and market surveillance tools have been strengthened, the growing use of adaptive and opaque AI models continues to challenge traditional oversight mechanisms. These developments underscore the need for robust testing, monitoring, and governance of AI-driven trading systems.

6 Portfolio management and robo-advisory services

Portfolio management has traditionally relied on frameworks derived from modern portfolio theory (MPT), which emphasizes diversification and the trade-off between risk and expected return (Markowitz, 1952). While MPT remains influential in institutional and retail investment management, its

assumptions of linear relationships, normally distributed returns, and static correlations limit its effectiveness in environments characterized by structural breaks and extreme events.

Artificial intelligence extends traditional portfolio frameworks by enabling non-linear modeling and dynamic adaptation to changing market conditions. Machine learning models can capture time-varying correlations, tail risks, and interactions across asset classes that are difficult to represent using static covariance matrices. Empirical evidence suggests that AI-enhanced portfolio strategies can improve risk-adjusted performance under certain conditions, particularly when incorporating alternative data and regime-dependent features (Heaton et al., 2017).

Large asset managers increasingly rely on AI-driven platforms to support portfolio construction, stress testing, and risk monitoring. These systems integrate macroeconomic indicators, market data, and firm-specific signals to evaluate portfolio exposures and rebalance positions dynamically. While such approaches offer enhanced flexibility, they also introduce new challenges related to model complexity, interpretability, and dependence on data quality.

Robo-advisors represent a prominent application of AI in retail finance. These digital platforms provide automated investment advice based on client characteristics such as risk tolerance, investment horizon, and financial goals. By automating portfolio construction and rebalancing, robo-advisors can reduce costs and improve diversification for retail investors. D'Acunto et al. (2019) found that robo-advisory services can enhance portfolio efficiency, although concerns remain regarding personalization, transparency, and investor understanding of algorithmic recommendations.

7 Risk management, fraud detection and regulatory compliance

Artificial intelligence plays an increasingly important role in financial risk management by enabling real-time monitoring of market, credit, and operational risks. Machine learning models can detect complex patterns and early warning signals that may be overlooked by traditional risk models, particularly in high-dimensional settings (Danielsson et al., 2017).

In market risk management, AI-based forecasting models have been applied to volatility estimation and Value-at-Risk (VaR) prediction. Empirical comparisons suggest that machine learning and deep learning models can outperform traditional VaR approaches in terms of predictive accuracy, particularly during periods of heightened market volatility (Huang et al., 2005). Unlike static models calibrated on historical distributions, AI-based risk systems can adapt dynamically as new information becomes available.

Fraud detection and anti-money laundering represent another major application area. Machine learning-based anomaly detection systems analyze large volumes of transactional data to identify suspicious behavior. Compared to rule-based approaches, these systems adapt more effectively to evolving fraud patterns and reduce false positives, improving both compliance

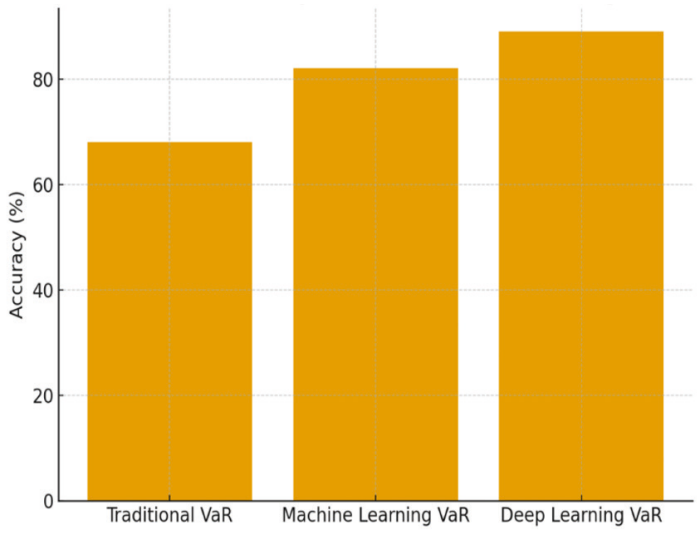
effectiveness and customer experience (Bolton and Hand, 2002).

Regulatory compliance has emerged as a critical domain for AI deployment, particularly in response to increasing regulatory complexity. Supervisory authorities emphasize explainability, accountability, and governance of AI systems used in regulated decisions. The European Union's Artificial Intelligence Act classifies many financial AI applications as high-risk, requiring institutions to demonstrate model transparency, robustness, and fairness. In the United States, regulators have expressed concerns about the potential for AI to mislead investors or amplify systemic risk.

These developments have led financial institutions to invest in governance structures such as model risk management frameworks, explainability tools, and internal AI ethics committees. Such mechanisms are intended to ensure that AI systems align with regulatory expectations and ethical standards while maintaining operational effectiveness.

Chart 5 summarizes findings from empirical studies comparing traditional Value-at-Risk models with machine learning and deep learning approaches. While results vary across datasets and market conditions, the literature consistently reports improved predictive performance for ML-based models, particularly during periods of elevated volatility. However, higher accuracy does not eliminate the need for stress testing and interpretability, especially in regulatory contexts. Deep learning models outperform traditional Value-at-Risk methods by over 20 percentage points. AI-based VaR systems adapt faster to volatility - essential in unpredictable markets like 2020 or 2023. For example, the Goldman Sachs reported a 15% improvement in daily P&L prediction accuracy after integrating ML-based risk engines.

Chart 5: Model accuracy in market risk forecasting



Source: Authors based on empirical findings from Huang et al. (2005)

Machine learning models process millions of loan applications or market data points in seconds, detecting patterns humans would overlook. For instance, JPMorgan's AI platform LOXM (JPMorgan Chase & Co., 2023) analyzes complex trading conditions across billions of historical and simulated transactions in real time to optimize trade execution and reduce costs compared with manual or rule-based methods, thus improving efficiency and accuracy in equities trading. Machine learning thrives here because it learns from new data and adapts, making it capable of responding quickly when a borrower's behavior changes overnight. Fintech platforms such as Zest AI (Scharfstein & Gilland, 2023) levevrage machine learning models to assess credit risk using vast and diverse datasets, enabling faster, more accurate underwriting decisions than traditional score-based methods and automating decisions that previously took days or weeks. Traditional models would still be asking for faxed pay stubs, whereas AI systems can integrate alternative signals and complex financial indicators to refine predictions. Although less publicly documented, major institutions including Goldman Sachs use internal AI and analytics teams to scan market data and flag emerging liquidity and risk signals ahead of traders, a practice noted in coverage of the use of AI tools in investment banking and risk analytics.

Traditional risk models use averages from the past, which works fine-until markets go rogue, as they did during the 2008 Global Financial Crisis (International Monetary Fund., 2009). In periods of extreme stress, such as sudden liquidity freezes or correlated asset sell-offs, traditional models struggle to adapt. Value-at-Risk (VaR) (Jorion, 2007), one of the most widely used market risk measures prior to 2008, significantly underestimated tail risks and failed to anticipate the magnitude of losses experienced by financial institutions during the crisis (International Monetary Fund, 2009; Jorion, 2007). These models do not learn from new information; they rely on fixed historical distributions and static assumptions.

In contrast, machine-learning-based risk models dynamically adapt as new data arrives, allowing them to respond to breaking news, market sentiment, and behavioral signals in near real time. BlackRock, for example, employs Aladdin (Financial Times, 2020), an AI-driven portfolio and risk management platform that continuously analyzes market volatility, stress scenarios, and liquidity conditions across global markets, enabling rapid portfolio adjustments during periods of heightened uncertainty (BlackRock, n.d.).

Similarly, JPMorgan Chase (Son, 2019) uses artificial intelligence to evaluate creditworthiness using thousands of structured and unstructured variables, moving beyond traditional credit scores to include transaction behavior, spending patterns, and real-time financial signals (JPMorgan Chase & Co. 2023). Its COiN (Contract Intelligence) platform applies natural language processing to legal documents and famously reviewed 12,000 commercial credit contracts in seconds, a task that previously required approximately 360,000 hours of manual legal review, dramatically reducing operational risk and human error (Son, 2019; JPMorgan Chase & Co., 2023).

Regulatory compliance represents another key application area. Supervisory authorities increasingly emphasize explainability, governance, and accountability of AI systems, particularly in the light of emerging regulations

such as the EU Artificial Intelligence Act. Balancing innovation with regulatory compliance remains a central challenge for financial institutions. Different regulators have different approaches regarding AI. While the EU through its AI Act defines strict rules on “High-Risk” (European Commission, 2024), across the Atlantic, the U.S. Securities and Exchange Commission (SEC) is looking into how AI might “influence or mislead investors” (SEC, 2023). This includes everything from credit scoring to fraud detection - all now under heavy compliance scrutiny (McKinsey & Company, 2024). European banks like BNP Paribas and Deutsche Bank have already begun “stress testing” their algorithms for bias and transparency. For SEC Wall Street’s new robot traders are on watch. The SEC is drafting AI risk disclosure rules, requiring financial firms to explain how they use algorithms in trading, advice, and credit decisions. Gary Gensler, the SEC Chair, even warned that “AI could trigger the next financial crisis if left unchecked” (Carter, 2023). Big names like Goldman Sachs and Morgan Stanley are now building compliance dashboards that track how AI models behave in real time.

Around the world, banks are realizing that having an AI Ethics Committee is not just good PR – it is survival. Institutions like HSBC, Citi, and UBS have formed teams that review algorithms for fairness, bias, and compliance before deployment. These committees combine tech, legal, and compliance experts - basically the Avengers of responsible AI. According to Deloitte, over 70% of top global banks now have internal AI ethics frameworks (Deloitte, 2023). Because in 2025, “we didn’t know what the AI was doing” (Reuters, 2025) is not an excuse that works with regulators.

8 Discussion: Implications for practice and policy

The evidence reviewed in this paper indicates that artificial intelligence has become a strategic capability in finance rather than a peripheral technological tool. However, improved predictive accuracy does not automatically translate into robust real-world performance. Financial environments are subject to regime changes, structural breaks, and feedback effects that can degrade model performance over time.

A central tension in AI adoption is the trade-off between model complexity and explainability. Highly complex models may deliver superior in-sample accuracy but pose challenges for transparency and accountability. Regulated financial decisions require models that are not only accurate but also interpretable and auditable. As a result, financial institutions increasingly combine performance objectives with governance requirements, including documentation standards, human oversight, and audit trails.

At the systemic level, widespread deployment of similar AI models can generate correlated behavior across institutions. If many firms rely on similar data sources and signals, market dynamics may become more procyclical, amplifying stress during adverse conditions. This systemic dimension suggests that micro-level governance must be complemented by macroprudential supervision that explicitly considers AI-driven interdependence.

8.1 Answers to the research questions

RQ1: Dominant application areas

The literature identifies six dominant application domains of AI in finance: (i) algorithmic and high-frequency trading, (ii) asset pricing and portfolio optimization, (iii) credit risk assessment, (iv) market and liquidity risk forecasting, (v) fraud detection and anti-money laundering, and (vi) regulatory compliance and supervisory technology. Trading and market microstructure applications dominate in early adoption due to speed and scalability requirements, while risk management, compliance, and fraud detection have grown rapidly in response to regulatory complexity and operational demands.

RQ2: Opportunities and risks

AI adoption offers significant opportunities through improved predictive accuracy, automation, scalability, and real-time decision-making. Empirical studies document performance gains in return prediction, credit scoring, and risk forecasting. However, these benefits are accompanied by substantial risks, including model opacity, algorithmic bias, data dependency, overfitting, and systemic procyclicality arising from correlated model behavior. The literature emphasizes that performance gains do not eliminate model risk and may, under stress, amplify financial instability.

RQ3: Governance and regulatory conditions

Responsible deployment of AI in finance requires robust governance frameworks encompassing model validation, explainability, documentation, monitoring, human oversight, and auditability. Emerging regulatory regimes, particularly the EU Artificial Intelligence Act and supervisory guidance from the BIS and U.S. regulators, emphasize accountability and transparency for high-risk financial AI applications. The literature converges on the view that governance quality is as critical as technical performance in determining the net impact of AI on financial stability.

9 Conclusion and future research

Artificial intelligence has emerged as a transformative force in modern finance, fundamentally reshaping how financial institutions allocate capital, manage risk, and interact with markets and clients. This paper has demonstrated that AI is no longer an experimental or auxiliary technology, but a core component of financial decision-making across trading, portfolio management, risk management, fraud detection, and regulatory compliance. By integrating insights from academic literature, industry evidence, and regulatory perspectives, the analysis highlights both the efficiency gains enabled by AI and the structural risks introduced by its widespread adoption.

From an operational and market perspective, AI systems significantly enhance speed, scale, and predictive accuracy. Machine learning and deep

learning models outperform traditional statistical approaches in environments characterized by high dimensionality, non-linearity, and rapid information flow, such as algorithmic trading, credit assessment, and real-time risk monitoring. Applications discussed in this paper-from AI-driven execution engines and robo-advisors to advanced Value-at-Risk models illustrate how financial institutions increasingly rely on adaptive algorithms to process vast datasets and respond dynamically to changing market conditions. These capabilities have become a source of competitive advantage and, in many cases, a necessity for survival in highly competitive global markets.

At the same time, the paper underscores that AI adoption fundamentally alters the risk profile of the financial system. Model opacity, algorithmic bias, data dependency, and pro-cyclical behavior introduce challenges that traditional governance and risk frameworks were not designed to address. The experience of the 2008 financial crisis highlights the limitations of static, historically calibrated models, while recent regulatory concerns emphasize that poorly governed AI systems may amplify rather than mitigate systemic risk. The increasing reliance on similar data sources and model architectures across institutions raises the possibility of synchronized behavior during periods of stress, posing new threats to financial stability.

The analysis further demonstrates that regulation and governance are becoming as important as technical performance. Emerging regulatory frameworks, such as the EU Artificial Intelligence Act and evolving supervisory approaches in the United States, reflect a growing recognition that AI in finance must be transparent, explainable, and accountable. Ethical oversight, model validation, and continuous monitoring are no longer optional but essential components of responsible AI deployment. Financial institutions that fail to integrate governance into their AI strategies risk not only regulatory sanctions but also reputational damage and operational failures.

Overall, this paper contributes to the literature by providing an integrated view of AI in finance that bridges technical innovation, economic theory, and regulatory policy. It argues that the future of AI in finance depends not solely on advances in algorithms or computing power, but on the development of robust institutional frameworks that align technological innovation with financial stability and societal trust. Future research should focus on explainable AI methods tailored to financial applications, empirical analysis of systemic interactions among AI-driven institutions, and the design of regulatory mechanisms that encourage innovation while mitigating systemic risk. Only through such an interdisciplinary and balanced approach can AI fulfill its potential as a force for sustainable and resilient financial innovation.

Use of Artificial Intelligence (AI) or AI-based Tools: *The authors disclose the use of Artificial Intelligence (AI) and/or AI-based Tools for language editing and text refinement during the preparation of this manuscript. The authors reviewed and edited all content and take full responsibility for the final work.*

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Artificial Intelligence in Banking: A Bibliometric Review of Risks, Regulation and Compliance Research (2011 - 2025)

Original scientific paper

Ivan Gržeta[1]

ABSTRACT

The rapid digital transformation of the financial industry has positioned artificial intelligence (AI) at the center of banking, risk management, and regulatory framework. The aim of this study is to give a complete and comparative bibliometric review and analysis of research on AI in banking, with a focus on risk, regulation, and compliance. The research goal is to examine its evolution through time, intellectual foundations, thematic structure, and geographical distribution,, while assessing the differences and similarities between two databases; Scopus and Web of Science (WoS). The study adopts a bibliometric research design covering the period 2011–2025. Two different datasets, with the same keywords, were taken from Scopus and WoS and analyzed using descriptive statistics, citation analysis, co-authorship and co-citation networks, keyword co-occurrence mapping, and thematic analysis. Data processing was conducted using Bibliometrix (R) and VOSviewer. The findings confirm a strong and sustained growth in scientific production, particularly after 2017. Both databases uncover a stable academic core centered on bankruptcy prediction, credit scoring, and machine-learning methodologies. The thematic structure converges around AI-driven risk modeling, fraud detection, and banking applications, while governance- and explainability-related themes remain emerging. Geographically, the research output is concentrated in a limited number of centers, primarily in China, the United States, the United Kingdom, and India. The study shows this field is methodologically mature but institutionally fragmented which emphasis the need for a better integration of governance, regulatory compliance, and explainable AI in future research.

Keywords: *Artificial intelligence, Banking, Risk management, Financial regulation, Compliance*

1 *Assistant Professor, University of Rijeka, Faculty of Economics and Business, Ivana Filipovića 4, 51000 Rijeka, Croatia. Scientific affiliation: University of Rijeka, Faculty of Economics and Business. Phone: +385 51 355 122 E-mail: ivan.grzeta@efri.uniri.hr*

JEL classification: *G21, G28, O33*

1 Introduction

Fast digital transformation of financial services have largely reshaped the structure and functioning of modern systems (Thottoli et al., 2023). Advances in financial technology, artificial intelligence, blockchain solutions and digital platforms have changed traditional models for financial intermediaries. However, those changes come with increased new forms of risk and regulatory complexity (Jia & Liu, 2024). As a result, financial technology, with emphasis on artificial intelligence, has become the central topic of both academic research and economic policies.

As it becomes a central topic, it has led to a substantial increase in scientific output connecting financial technology with traditional institutions. The literature spans in multiple disciplines, from economics to finance, information systems, computer science etc., proving thus the interdisciplinary nature of the field. While such diversity enriches academic debate, at this early stage, it fragments the body of knowledge, with limited integration between disciplines and methodology approaches.

The existing bibliometric studies provide valuable insights into this new field, however, several limitations remain. Most of the studies rely solely on a single bibliographic database, with relatively short time horizons (Huda et al., 2026; Saputri et al., 2025). Differences in database coverage, for example, relying on a single database, may lead to a partial or biased representation of this technologically intensive and rapidly developming area. In such an environment, these limitations can reduce ability to draw robust conclusions about where the research area is heading, and what the core trends, influential contributions and research gaps are.

The objective of this paper is to give a complete bibliometric analysis of scientific work in the fields of artificial intelligence, financial institutions and risk management, over the period between 2011 to 2025, by using two complementary bibliographic databases, Scopus and Web of Science. By analysing the two databases in parallel, this paper aims to offer a more balanced and robust overview of the development of this research area. The contribution of this paper is threefold. First, it shows temporal evolution, geographic distribution and publication journals within this field. Second, it compares the thematic structure identified in Scopus and Web of Science, highlighting their complementary importance. Third, it provides valuable insights not only for researchers but also for regulators and policymakers that seek to better understand this growing literature underpinning digital transformation in finance.

Based on the literature and the research gaps, the following hypotheses are formulated:

> **H1**: Scientific production in the fields of artificial intelligence, banking and risk management exhibits a strong and sustained growth, particularly after 2017.

H2: Scopus and Web of Science provide different but complementary representations of the research field.

H3: The thematic structure of fintech research converges around a limited number of stable clusters.

The conceptual novelty of this study lies in three elements. First, it explicitly positions risk management, regulation, and compliance as the central analytical lens within AI–banking research, while most existing bibliometric studies examine artificial intelligence only as part of broader fintech ecosystems. Second, the study conducts a systematic, parallel comparison between Scopus and Web of Science, which remains rare in the existing literature. Third, by combining citation networks, thematic mapping and geographical collaboration analysis, the study provides a policy-relevant interpretation of the field's intellectual structure, highlighting the gap between algorithmic innovation and regulatory integration.

The remainder of the paper is organised as follows. Section 2 reviews the relevant literature. Section 3 presents the data sources and the methodological framework. Section 4 reports and compares the empirical results obtained from Scopus and Web of Science. Section 5 discusses the main findings and outlines directions for future research, while the final section concludes the paper.

2 Literature review

The rapid growth of artificial intelligence has generated a large body of academic literature. With regards to the banking industry, research has explored a wide range of applications, including credit scoring, fraud detection, automated trading, customer experience, regulatory compliance and risk management (Aziz & Andriansyah, n.d.; Bhattacharya & Sinha, 2022; Editor, 2024; Mathen & Paul, 2025). However, the increase of this literature has been unequal across themes, disciplines, and publication journals, therefore making systematic mapping important.

2.1 Bibliometric and review studies on AI and banking

A significant number of existing bibliometric analyses and research focus on the development of fintech, digital finance, blockchain and financial inclusion (Del Sarto & Ozili, 2025; Firdaus et al., 2019), often considering artificial intelligence as a component within a broader ecosystem. Such research typically display a strong growth in scientific papers after the mid-2010s, indicating fast digital transformation and bigger interest in the new technologies applicable in finance.

The analyses provide valued insights into publication trends, influential authors, and dominant clusters; however, their thematic emphasis can be skewed toward innovation, and less toward applications in financial industry. Issues related to risk management or regulatory compliance are often treated as secondary topics. As a result, the regulatory and risk management

standpoint of artificial intelligence adoption in banking remain shattered in the bibliometric literature.

A smaller subset of review studies has begun to address risks related to artificial intelligence more explicitly (Oke & Cavus, 2025). These contributions highlight that artificial intelligence systems may help in managing risks or fraud detection. Nevertheless, most papers approach these issues conceptually without providing a comprehensive mapping of how risk, regulation, and regulatory compliance are structured within the broader AI-banking research field.

2.2 Data sources and methodological approaches in prior bibliometric research

From a methodological point of view, most bibliometric analyses show several characteristics. The majority of them rely on a single bibliographic database, most frequently Scopus (Huda et al., 2026; Kumar et al., 2024; Saputri et al., 2025; Singh, 2023) or, less often Web of Science (Oke & Cavus, 2025). While both databases are widely recognized and used, their coverage differs substantially in terms of indexed journals, conference proceedings, disciplinary orientation, etc. Using a single database therefore risks providing a partial or biased representation of the research field particularly in interdisciplinary and novelty areas such as artificial intelligence and banking.

Existing bibliometric research commonly combines descriptive indicators with network techniques to capture publication dynamics, co-citations, thematic structures etc. Descriptive measures are core in analyses as they give an effective overview of growth patterns. At the same time, more advanced methods are increasingly used to reveal connections and theoretical development within the field, with the variation of their application between studies (Ahmed et al., 2022; Roy et al., 2025)

The time horizon in general for bibliometric analyses is quite short, since the usage of AI technologies and their implication in banking and finance is considered a novelty. Because of that most of the studies focus on the post-2015 period, after which scientific output began to increase (Ahmed et al., 2022; Fundira & Mbohwa, 2025; Mostafa, 2025). Rather than representing a limitation, this concentration reflects the evolutionary stage and the novelty of the field which additionally highlights the importance of continuously updating bibliometric evidence to capture ongoing shifts in research trends.

2.3 Gaps in the literature and the positioning of the present study

The existing literature reveals several important gaps. Most notably, there is a lack of bibliometric studies that explicitly foreground risk management, regulation, and compliance as core analytical lenses in the examination of AI adoption in banking. These topics are currently on the increase in policy debates and regulatory frameworks, bur are currently underrepresented in mappings of academic research. Furthermore, few studies conduct parallel

and systematic comparisons between Scopus and Web of Science, despite clear evidence that these databases capture different segments (Pranckutė, 2021). This limitation is particularly important for research in multidisciplinary fields, or in this case, at the intersection of AI, banking, and regulation.

To address these limitations, the present study conducts a comparative bibliometric analysis of AI-related research in banking with a specific focus on banking, risk, regulation, and compliance. By jointly employing Scopus and Web of Science data and by applying a combination of descriptive, network-based, and thematic analyses, the study aims to provide a more balanced and policy-relevant mapping and insight into the evolution of this research area.

3 Methodology

This paper adopts a qualitative and descriptive-analytical research design aimed at systematically examining the selected research phenomenon through a structured review and synthesis of relevant academic sources. Given the exploratory nature of the topic and the heterogeneity of existing contributions, the analysis does not rely on econometric modeling, but instead applies an integrative analytical framework that allows for the identification of dominant themes, conceptual approaches and emerging research directions.

3.1 Research design, data sources and selection criteria

This paper adopts a bibliometric research design aimed at systematically mapping and comparing the scientific literature on the selected research topic. Bibliometric methods are used to identify publication trends, citation patterns, and the intellectual structure of a respective field based on structured metadata.

The analysis covers the period 2011–2025, which captures both the early development phase and the rapid expansion of research activity in the observed domain. The object of the analysis consists of individual scientific publications indexed in the selected bibliographic databases. Each publication is treated as a single observation and analyzed based on its bibliographic information, including authorship, publication year, source, citations, and keywords.

Built on the study of Bernardelli and Giudici (2025) the data preparation and analysis were conducted according to a systematic and replicable sequence of steps:

1. Selection of databases: Two bibliographic databases, Scopus and Web of Science (WoS), were used in the analysis in order to obtain a more comprehensive and comparable overview of scientific output. Scopus is known for its broad thematic and disciplinary coverage, as well as for its strong inclusion of conference proceedings, book chapters, and interdisciplinary journals, which is particularly relevant for rapidly growing and technology-intensive research areas. WoS indexes a smaller but more selective set of journals with higher

average impact factors. The parallel use of both databases reduce the limitations of relying on a single source, enhances the robustness of the findings, and enables a systematic comparison of how different indexing policies affect the visibility. The search was performed in September 2025.

2. Search strategy: The search was conducted using combinations of the following keywords: “artificial intelligence”, “AI”, “machine learning”, “deep learning”, as well as “banking”, “banks”, “financial institutions” and “risk”, “regulation”, “compliance” “risk management”). To be more precise, exact search string for WoS was *TS = ((“artificial intelligence” OR “AI” OR “machine learning” OR “deep learning”) AND (“banking” OR “banks” OR “financial institutions”) AND (“risk” OR “regulation” OR “compliance” OR “risk management”))*, while for Scopus *TITLE-ABS-KEY ((“artificial intelligence” OR “AI” OR “machine learning” OR “deep learning”) AND (“banking” OR “banks” OR “financial institutions”) AND (“risk” OR “regulation” OR “compliance” OR “risk management”))*. In Scopus, the analysis included research articles, review papers, conference papers, and book chapters, while in WoS, research articles, review papers, conference papers, and early access publications. This approach ensured comprehensive coverage of all relevant publications within the defined research domain.
3. Inclusion criteria: Only publications written in English and belonging to relevant subject areas were included in the corpus. In Scopus, these subject areas were Business, Management and Accounting; Economics, Econometrics and Finance; Computer Science; Decision Sciences; Engineering; and Social Sciences. In WoS, the following categories were used: Business Economics; Computer Science; Engineering; Government Law; Social Sciences and ther Topics; and Operations Research & Management Science.
4. Data extraction: Metadata (authors, affiliations, keywords, sources, publication years, and citations) from both databases were exported in formats compatible with bibliometric analysis.
5. Data processing: The dataset was imported into R and processed using the Bibliometrix package. Duplicate records were identified and removed using the Bibliometrix duplicatedMatching function. VOSviewer was employed for network analysis and visualization.
6. Analysis: First the descriptive statistics were analysed (overall scientific output, citations, most productive countries, authors, and sources), followed by network analysis (co-authorship, co-citation, and keyword co-occurrence). Additional visualizations and graphical representations were also presented.
7. Interpretation: The results were interpreted through a comparative analysis of Scopus and WoS. Overlay and thematic analyses enabled the identification of emerging research topics.

The combined methodological approach provides a transparent and replicable

framework for mapping scientific output and identifying structural patterns across both databases. The following section presents the empirical results, beginning with descriptive statistics, followed by analyses of authorship, collaboration, co-citation, and thematic patterns.

3.2 Analytical methods and tools

The analysis is done using a mixture of bibliometric methods and specialized tools. Bibliographic data were processed and analyzed primarily using R software, with the Bibliometrix package used primarily for descriptive statistics. Network-based visualizations such as co-authorship, co-citation and keyword co-occurrence maps, were made using VOSviewer software. In the network visualizations, generated using VOSviewer, minimum occurrence thresholds were applied to improve clarity and interpretability of the results. Specifically, in the keyword co-occurrence analysis, only keywords with a minimum occurrence of 20 were included in the network. This threshold was selected to reduce noise from infrequent terms and to focus on the most structurally relevant and representative concepts within the research field.

For the analysis, the bibliographic metadata were firsly extracted from the two databases and imported into R software. Then data cleaning was performed to address possible inconsistencies. Later, the descriptive indicators were calculated and network and thematic analyses were conducted to identify collaboration patterns, academic structures and the evolution of research themes.

Despite the robustness of the applied methods, i.e. using two databases and two software tools, several methodological limitations should be addressed. The results of a bibliometric analysis depend on indexed metadata which may not completely capture the impact of observed studies. Furthermore, the measures that are based on citation can be subject to delayed effects that can underestimate the influence of publications. And lastly, the analysis is limited to publications in the English language which may exclude relevant regional outputs.

4 Empirical data and analysis

This chapter presents the empirical findings obtained through bibliometric analysis. The results are structured to first cover descriptive statistics, followed by a focus on comparisons between databases and patterns of scientific output.

4.1 Descriptive statistics and basic characteristics of the dataset

As previously mentioned, two separate datasets were collected for the Scopus and Web of Science databases. In the WoS database, the final dataset comprises 1,000 documents, with an annual growth rate of 34.74%. The average age of a document is 2.74 years, and each document receives

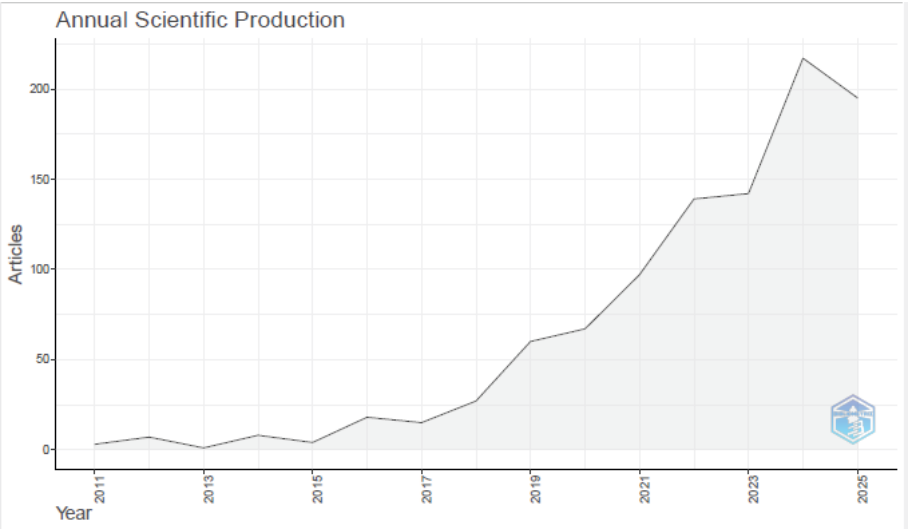
an average of 12.48 citations. The dataset includes publications from 555 different sources (journals, books, etc.) and contains a total of 1,035 authors' keywords. The collection consists primarily of original research articles (690) and proceedings papers (203). A relatively large number of review articles (43) and early access papers (49) is also recorded, while other document types are present in smaller numbers. The dataset reflects contributions from 2,919 authors, of whom 108 published single-authored papers. On average, each document has approximately 3.22 co-authors, and the share of international co-authorship is 25.2%. This indicator reflects the level of international research collaboration, with higher values typically indicating more intensive knowledge exchange across countries. In this case, the results point to a moderate level of internationalization, alongside a substantial share of domestic or national collaborations.

For the Scopus database, the summary of statistical indicators is as follows. The final dataset includes 2,476 documents, with an annual growth rate of 27.48%. The average age of a document is 2.59 years, and the average number of citations per document is 10.87. The dataset comprises publications from 717 different sources and contains a total of 12,112 authors' keywords. The collection consists primarily of journal articles (1,215), followed by conference papers (1,206), and review papers (55). A total of 7,708 authors contributed to this dataset, with 265 authors publishing single-authored papers. On average, each document has approximately 3.4 co-authors, while the share of international co-authorship amounts to 20.4%.

4.2 Temporal and structural trends

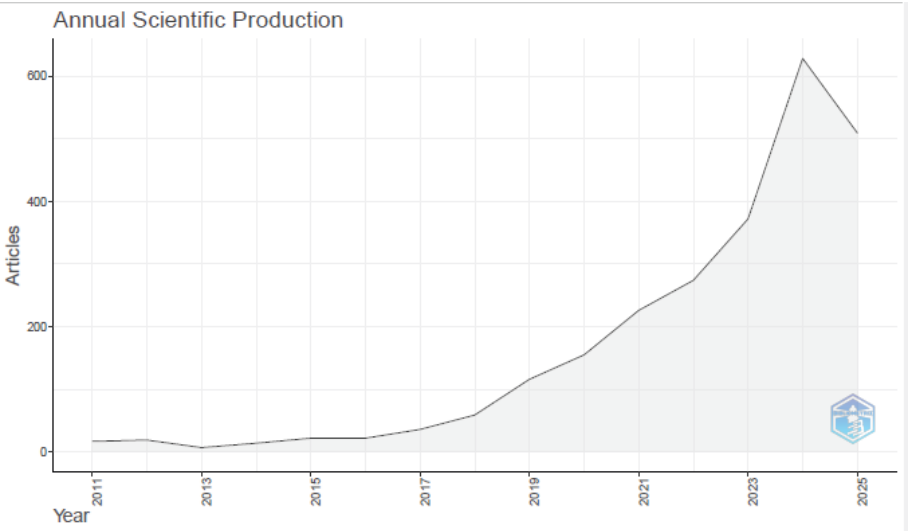
Annual publication trends exhibit an accelerated growth pattern in both databases, WoS (Figure 1) and Scopus (Figure 2), particularly from 2018 onwards. In both databases, the number of publications reaches its highest levels in the most recent years, with clear indications of a continued upward trajectory. This pattern reflects the growing relevance of fintech, digital finance, and related technological applications in academic discourse, regulatory frameworks, and industry practice.

Figure 1: Annual scientific production, WoS database



Source: Author

Figure 2: Annual scientific production, Scopus database



Source: Author

A comparative analysis of the two databases was conducted to assess the consistency of the empirical results. Despite differences in coverage and indexing policies, both databases exhibit highly similar empirical patterns. In particular, both databases display an almost identical publication trend,

characterized by an obvious and continuous growth starting in 2018, highlighting the novelty and rapid maturation of artificial intelligence in banking, as a research field. The average number of citations per publication is comparable across the two databases. Minor deviations can be attributed to differences in source composition and indexing timing; however, these do not alter the overall similarity of citation patterns.

4.3 Most cited papers and intellectual foundations

The assessment of the most cited papers across Web of Science and Scopus highlights a consistent intellectual backbone. The concentration of citations around a limited number of papers confirms the presence of a stable and well-defined research foundation.

In the Table 1, the four most cited papers in the WoS dataset are presented, while table 2, presents the 4 most cited papers in the Scopus dataset. These tables represent highly influential works regularly referenced across studies. Publications shown in table define key conceptual frameworks, influential research themes and methodological reference points within the analyzed field.

Table 1: Most cited papers in the WoS database

Authors	Paper	Journal	Year
Tianqi Chen, Carlos Guestrin	XGBoost: A Scalable Tree Boosting System	Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining	2016
Stefan Lessmann, Bart Baesens, Hsin-Vonn Seo, Lyn C. Thomas	Benchmarking state-of-the-art classification algorithms for credit scoring: An update of research	European Journal of Operational Research	2015
Edward I. Altman	Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy	The Journal of Finance	1968
Scott M. Lundberg, Su-In Lee	A unified approach to interpreting model predictions	Proceedings of the 31st International Conference on Neural Information Processing Systems	2017

Source: Author

Table 2: Most cited papers in the Scopus database

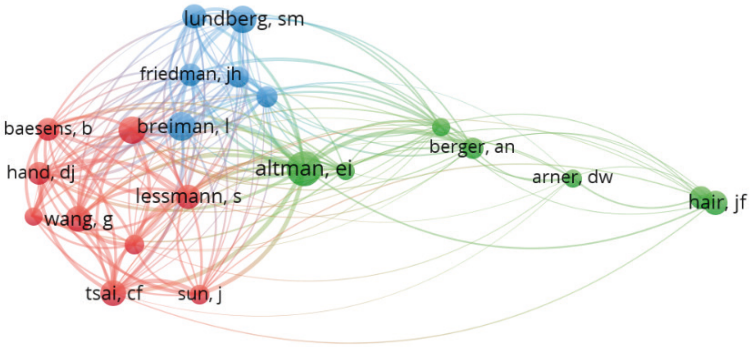
Authors	Paper	Journal	Year
Edward I. Altman	Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy	The Journal of Finance	1968
Leo Breiman	Random Forests	Machine Learning	2001
Tianqi Chen, Carlos Guestrin	XGBoost: A Scalable Tree Boosting System	Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining	2016
B Baesens, T Van Gestel, S Viaene, M Stepanova, J Suykens &J Vanthienen	Benchmarking state-of-the-art classification algorithms for credit scoring	Journal of the Operational Research Society	2001

Source: Author

Importantly, the comparison between the two databases reveals a strong overlap. The majority of the most cited works appear in both WoS and Scopus rankings. In particular, (Altman, 1968; Chen & Guestrin, 2016; Lessmann et al., 2015) are consistently positioned among the most influential contributions in both datasets. This confirms the presence of a stable intellectual core and reinforces the robustness of the bibliometric findings, indicating that the field's foundational literature is not database-dependent but structurally consolidated across major indexing platforms.

Figure 3 and Figure 4 illustrate the co-citation network of authors and sources in WoS database. Each cluster represents a group of studies that share common theoretical roots or thematic focus.

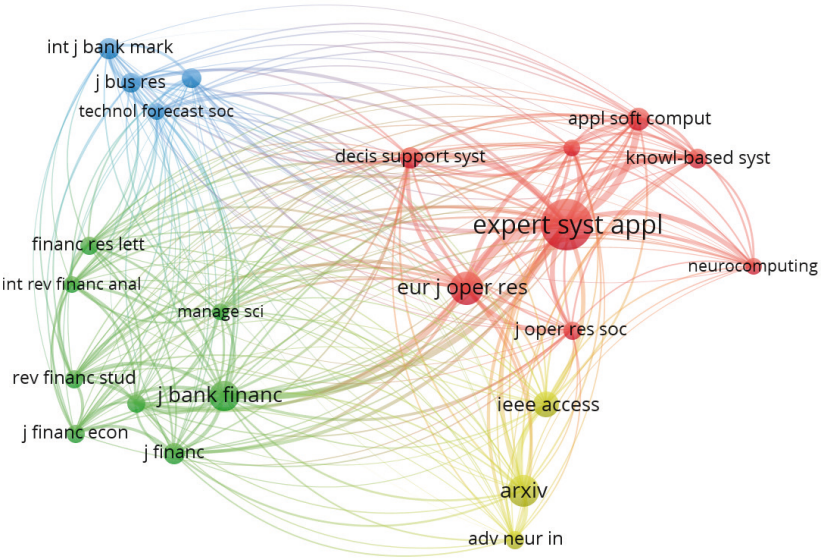
Figure 3: Co-citation network of authors, WoS database



Source: Author

The author co-citation network reveals several clearly defined clusters. Foundational scholars such as Altman, Breiman, Friedman, Lundberg, and Baesens occupy central bridging positions, linking classical bankruptcy prediction, ensemble learning, and explainable AI streams. The clustering structure confirms the existence of a consolidated intellectual core combining statistical credit risk modeling and advanced machine learning approaches.

Figure 4: Co-citation network of sources, WoS database

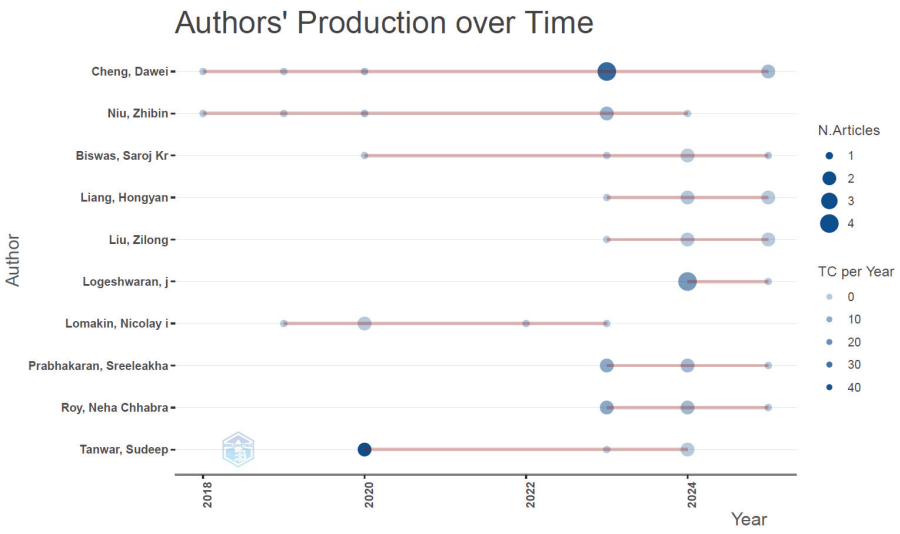


Source: Author

The WoS journal co-citation network displays a structurally similar intellectual backbone to Scopus, but with greater dispersion toward interdisciplinary and technical outlets. Alongside core finance journals, stronger visibility is given to journals in expert systems, decision support systems, applied computing, and operational research (e.g., Expert Systems with Applications, Decision Support Systems, Applied Soft Computing). This suggests that WoS captures a broader spectrum of applied and computational contributions.

Turning to the Scopus database, Figures 5 and 6 provide complementary insights.

Figure 5: Author's production over time, Scopus database



Source: Author

Figure 5 shows how the most productive authors indexed in Scopus have changed over time. There has been a lot of publication activity in the last several years, suggesting that the study and research area is growing. Several authors display continuous productivity across several years, with the rising citation intensity that indicates an increasing academic influence and the rapid advancement of AI-driven research.

Figure 6: Co-citation network of sources, Scopus database



Source: Author

The Journal of Finance, the Journal of Financial Economics, the Review of Financial Studies, and the Journal of Banking and Finance are the main financial journals that make up the network, while other research journals help connect the dots. The Scopus structure seems to be mostly made up of high-impact, theory-based finance and management journals. This suggests that it

is well-grounded in existing financial economics literature.

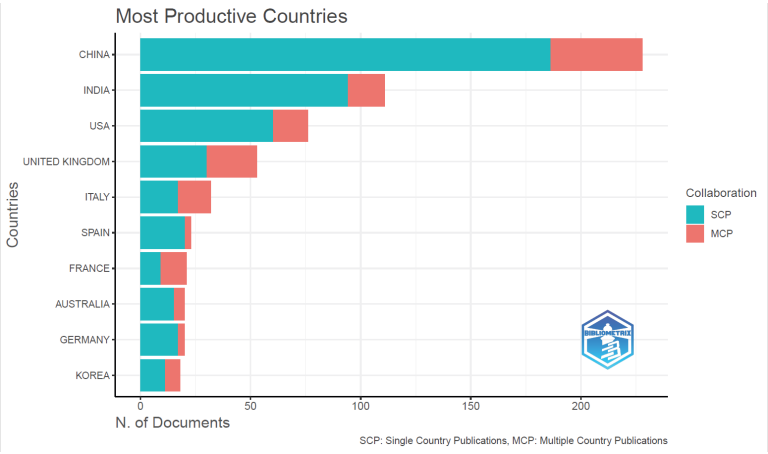
Even though there are some little discrepancies in their structures, both WoS and Scopus hint to a clear and shared intellectual structure. Scopus appears slightly more concentrated around traditional, high-impact finance and management journals, whereas WoS reflects stronger integration with computational and decision-support disciplines. Despite this, the convergence of both datasets shows that AI-driven credit risk research is now a big part of mainstream finance and is growing into more practical and transdisciplinary areas.

4.4 Productivity and collaboration patterns

This subsection analyzes the social structure of scientific production by jointly examining research productivity and collaboration patterns across countries. The objective is to identify where research is concentrated and how international collaboration networks shape the field.

Productivity indicators provide insight into the geographical concentration of research activity, while co-authorship networks illustrate the intensity and structure of scientific collaboration. Figure 7 and Figure 8 present the most productive countries in the analyzed datasets enabling the comparison between the two datasets, and highlighting those that act as central contributors to the field.

Figure 7: Most productive countries, WoS database

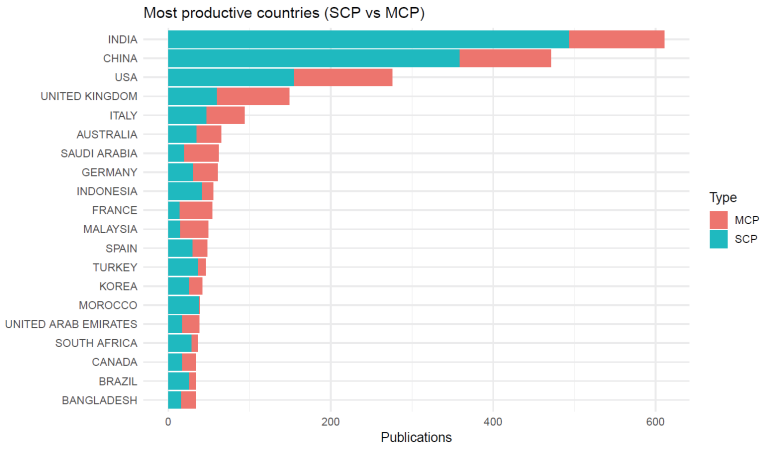


Source: Author

The Web of Science results show that China, India, and the United States are the most productive countries. China demonstrates particularly strong single-country publication (SCP) dominance, indicating substantial domestic research capacity. The United States and the United Kingdom also maintain high output levels, combining domestic productivity with meaningful international

collaboration. European countries such as Italy, Spain, France, and Germany appear as secondary but stable contributors.

Figure 8: Most productive countries, Scopus database

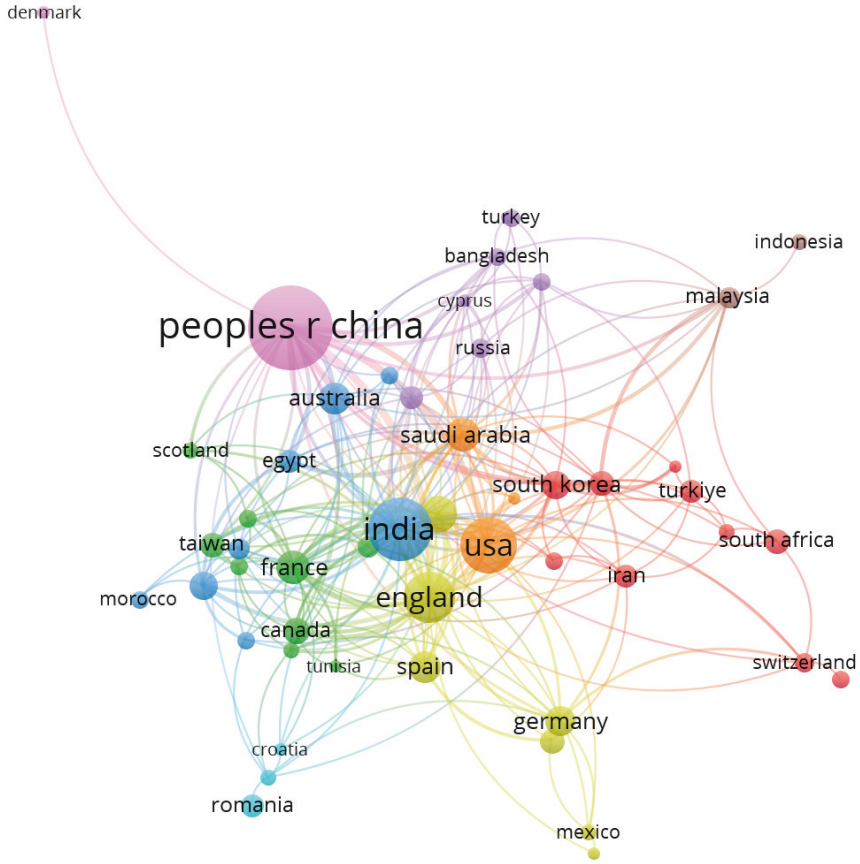


Source: Author

The Scopus productivity ranking largely mirrors the WoS structure. India, China and the United States remain the leading producers, followed by the United Kingdom and Italy. The SCP–MCP (single-country vs. multiple-country publications) comparison confirms that major research economies combine strong internal production with cross-border collaboration. However, Scopus reveals slightly broader participation from countries such as Saudi Arabia, Indonesia, Malaysia, and Turkey, reflecting its wider coverage of regional and applied research outlets.

To complement productivity indicators, co-authorship networks further clarify the structural position of countries within the global collaboration landscape, shown in Figure 9 for WoS and Figure 10 for the Scopus databases.

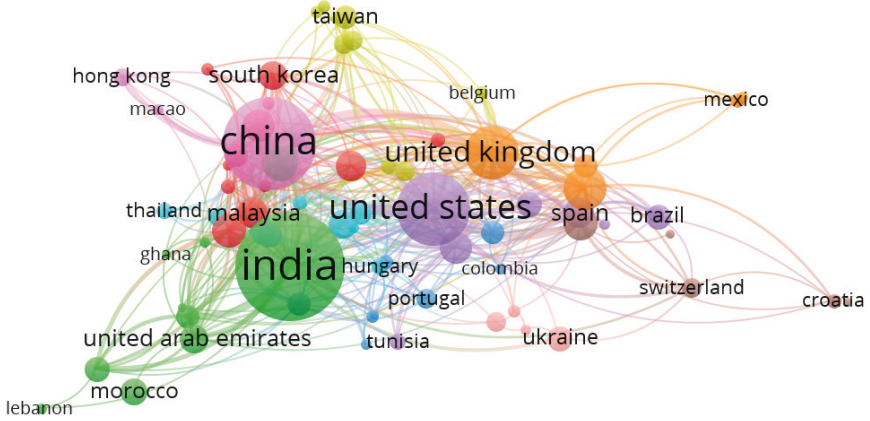
Figure 9: Co-author countries, WoS database



Source: Author

The WoS collaboration network highlights China, India and the United States as central connectors within the global research system. China occupies a structurally prominent position but appears somewhat more nationally concentrated compared to Western hubs. India emerges as an increasingly influential and well-connected actor, bridging multiple regional clusters. European countries form dense interlinked sub-networks, reinforcing intra-European collaboration.

Figure 10: Co-author countries, Scopus database



Source: Author

The Scopus collaboration network displays a similar overall structure but appears more dispersed and inclusive. While the United States, China, and India remain central hubs, there is stronger visibility of emerging research communities in the Middle East, Southeast Asia, and parts of Africa. Countries such as Malaysia, Indonesia, Turkey, and Saudi Arabia are more clearly integrated into the network.

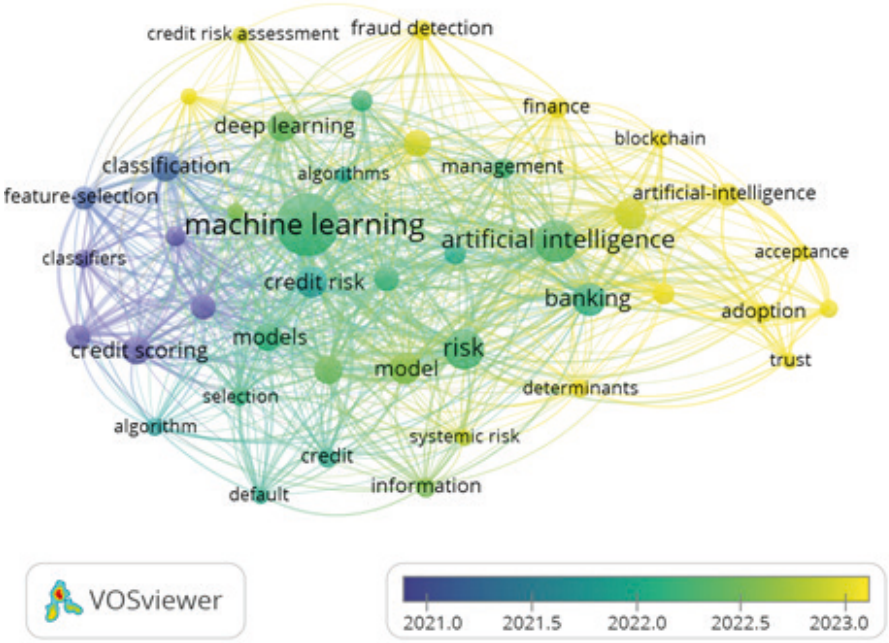
Both Web of Science and Scopus converge on a consistent conclusion. The field is geographically concentrated in a limited number of dominant research hubs, primarily China, the United States, the United Kingdom and India, while other countries participate mainly through collaborative ties. The strong structural similarity across the two databases reinforces the robustness of the geographical findings and indicates that AI-driven financial risk research is internationally interconnected yet asymmetrically distributed across major scientific economies.

4.5 Thematic structure of the research field

This subsection examines the thematic composition and conceptual organization of the research field by combining keyword co-occurrence analysis, word-frequency visualization, and thematic mapping. Together, these approaches provide insight into both the dominant research topics and their relative structural importance and maturity within the literature.

Keyword co-occurrence analysis captures the interconnected structure of the field by identifying the most frequently used and relationally embedded terms. Figures 11 and 12 present the Web of Science (WoS) results, including the keyword network and word cloud.

Figure 11: Co-occurrence keywords, WoS database



Source: Author

The WoS network shows a stable and strong core structured around machine learning, artificial intelligence, risk and banking. Central nodes are linked with fraud detection, deep learning, models and credit scoring, which indicates a research focus on predictive modeling in banking and the financial industry. The temporal overlay further suggests a steady shift toward newer themes such as blockchain, trust and adoption, which reflects the increase in the attention to integration and governance of modern technology.

Figure 12: Wordcloud, WoS database

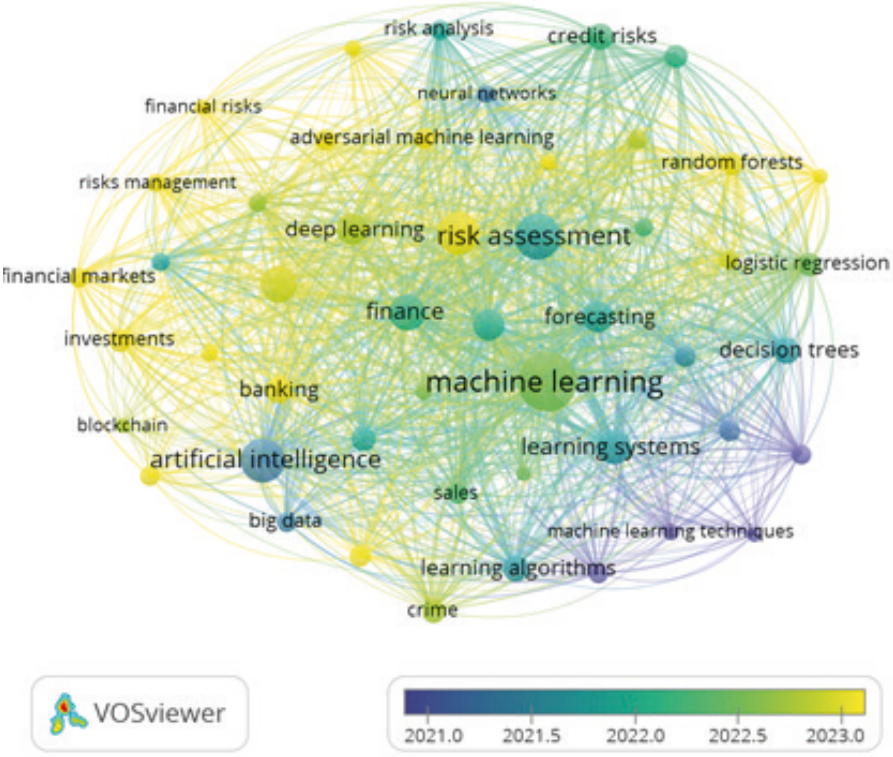


Source: Author

The WoS word cloud reinforces this structure, highlighting artificial intelligence, credit risk, credit scoring, risk management, and fintech as dominant terms. The prominence of both financial and computational concepts confirms the interdisciplinary yet finance-anchored nature of the field.

Figures 13 and 14 present the corresponding results for the Scopus database.

Figure 13: Co-occurrence keywords, Scopus database



Source: Author

The Scopus keyword network displays a similar core configuration, again centered on machine learning and artificial intelligence, but with stronger emphasis on risk assessment, finance, and algorithm-specific terms such as random forests, logistic regression, and decision trees. The structure appears more methodologically granular.

Figure 14: Wordcloud, Scopus database



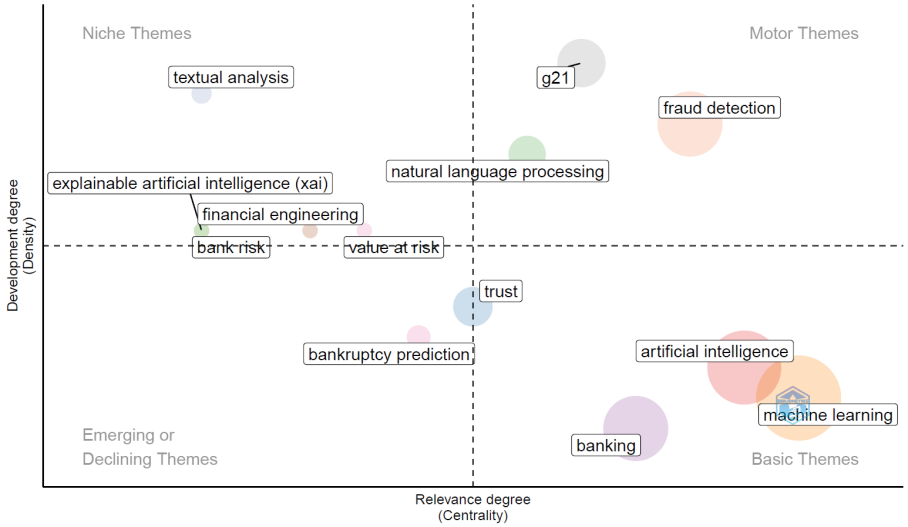
Source: Author

The Scopus word cloud confirms the dominance of risk assessment, machine learning, deep learning, and financial institutions, indicating a slightly stronger orientation toward operational risk analytics and implementation-focused research.

Comparatively, Web of Science appears more concentrated around finance-oriented terminology (e.g., credit risk, risk management, financial institution), while Scopus shows greater dispersion toward algorithmic specificity and computational techniques. Nevertheless, the overlap between the two databases is substantial. Both clearly converge on a thematic backbone defined by AI-driven credit risk modeling, fintech integration, fraud detection, and advanced learning methods. This convergence strengthens the robustness of the thematic findings and suggests that differences reflect database coverage characteristics rather than conceptual divergence.

To further examine thematic maturity and structural positioning, Figure 15 presents the thematic map based on the WoS dataset.

Figure 15: Thematic map, WoS database



Source: Author

The thematic map positions research themes according to their centrality (relevance within the field) and density (level of internal development). Based on the WoS database, in the upper-right quadrant (Motor Themes), fraud detection and G21 (banking) appear as highly central and well-developed topics which indicates that they drive research dynamics. The lower-right quadrant (Basic Themes) includes machine learning, artificial intelligence, and banking, which are also highly central, but conceptually broad, meaning that they function as foundational pillars of this research field.

The upper-left quadrant (Niche Themes) contains textual analysis and explainable artificial intelligence (XAI), suggesting specialized subfields that are less included in the mainstream. Moreover, the explainable artificial intelligence (XAI) theme, which is centrally positioned, signals increasing relevance in regulatory transparency. In the lower-left quadrant (Emerging or Declining Themes), bankruptcy prediction, and partially trust and risk display lower centrality and density. Rather than indicating decline, this positioning can reflect a methodological transition from traditional statistical dominance toward AI-enhanced extensions, especially in the trust field, as indicated in Figure 11.

The combined keyword networks, word clouds, and thematic maps confirm that the research area is organized around a strong methodological core centered on AI and machine learning, while gradually expanding toward the interpretability and regulatory (compliance) oriented area. The strong structural similarity between WoS and Scopus further validates this thematic stability and maturity.

5 Results and discussion

This section presents and interprets the main findings of the bibliometric analysis. By integrating citation structures, thematic configurations, and geographical collaboration patterns across Web of Science and Scopus, the results provide a comprehensive representation of the intellectual foundations, thematic evolution, and structural dynamics of research on artificial intelligence in banking and credit risk.

The empirical findings allow a direct evaluation of the proposed hypotheses:

- H1: Scientific production in the fields of artificial intelligence, banking and risk management exhibits strong and sustained growth, particularly after 2017.
- The descriptive statistics and annual publication trends in both Scopus and Web of Science confirm this pattern, showing accelerated growth from 2018 onwards. H1 is therefore confirmed.
- H2: Scopus and Web of Science provide different but complementary representations of the research field. The comparative analysis reveals strong structural similarities in publication trends, thematic clusters, and citation structures, while also highlighting differences in database coverage and disciplinary orientation. H2 is therefore confirmed.
- H3: The thematic structure of fintech research converges around a limited number of stable clusters.

Keyword co-occurrence networks and thematic mapping clearly demonstrate the presence of a stable core centered on machine learning, credit risk, and banking applications. H3 is therefore confirmed.

5.1 Interpretation of key findings

The bibliometric data from Scopus and Web of Science show a very consistent citation structure. This shows that the databases are coming together and strengthens the academic intellectual core of the field. In both datasets, citations are centered around a limited number of important works, creating dense and stable co-citation clusters. This pattern indicates that the research on bankruptcy prediction and credit risk modeling is rooted in a coherent methodological framework rather than scattered across disparate avenues. Foundational contributions serve as shared reference points, influencing both conceptual frameworks and empirical benchmarks in subsequent research.

At the heart of this intellectual core is Altman (1968), whose Z-score model instituted the quantitative paradigm of corporate failure prediction through financial ratios and analysis. The enduring centrality and importance of this work in both databases highlights the influence of statistically grounded and interpretable models. This foundation was systematized in consumer credit contexts by Hand and Henley (1997), who reviewed statistical classification

methods and emphasized the domain-specific constraints of credit scoring. The benchmarking tradition gained methodological rigor with Baesens et al., (2003), who demonstrated through systematic comparison that both simple (logistic regression, LDA) and more advanced (neural networks, SVM) classifiers can achieve strong predictive performance. This line of inquiry was further refined by Lessmann et al., (2015), who incorporated newer algorithms and evaluation metrics while explicitly questioning whether incremental improvements in accuracy translate into managerial relevance. Together, these contributions define a coherent cluster focused on performance evaluation, methodological comparison, and empirical robustness.

A second major cluster, equally visible in Scopus and Web of Science co-citation networks, reflects the rise of ensemble and boosting techniques. Breiman (2001) introduced Random Forests as robust ensembles of decorrelated trees with internal error estimation and variable importance measures, emphasizing stability and noise resistance. In parallel, Friedman (2001) formalized Gradient Boosting Machines as stagewise additive expansions optimized in function space, providing both theoretical grounding and interpretability tools. This trajectory culminates in Chen and Guestrin (2016), whose XGBoost framework combined algorithmic efficiency with systems-level scalability, enabling large-scale deployment and establishing, boosting, as a dominant paradigm in applied machine learning. Within credit scoring specifically, Abellán and Castellano (2017) demonstrated that ensemble performance depends critically on the choice of base classifier and uncertainty handling, challenging the simplistic assumption that the individually strongest learner is always optimal in an ensemble setting.

A third interconnected stream links methodological innovation with applied financial risk forecasting and structural data challenges. Khandani et al.(2010) showed that nonlinear machine-learning models significantly improve out-of-sample delinquency forecasts and produce economically meaningful cost reductions, while also suggesting broader systemic risk applications. Earlier, Angelini et al. (2008) analyzed the effectiveness of neural networks in regulatory credit-risk contexts, and provided careful preprocessing and validation procedures are implemented. Chawla et al. (2002) showed that a combination of their method of over-sampling the minority class and under-sampling the majority class can achieve better classifier performance. More recently, Addo et al.(2018) compared machine and deep learning models and found tree-based methods to be more stable than multilayer neural networks, raising critical questions about the uncritical adoption of deep learning in enterprises. Complementing these applied studies, Duarte and Barboza (2020) evaluate the various academic research with multiple views on credit risk and artificial intelligence (AI) and their evolution.

As model complexity increased, interpretability emerged as a structural concern, particularly in regulated financial environments. Lundberg and Lee (2017) addressed this tension by proposing SHAP, a unified framework for additive feature attribution, thereby integrating explainability into complex models. The prominence of this contribution within co-citation clusters underscores the field's recognition that predictive power alone is insufficient without transparency and accountability.

The combined Scopus and Web of Science evidence indicates that the field is methodologically mature, characterized by a stable and coherent intellectual core spanning statistical foundations, benchmarking traditions, ensemble dominance, imbalance correction, and explainability frameworks. However, despite this algorithmic sophistication, the literature remains institutionally fragmented. While predictive performance has steadily improved from discriminant analysis to scalable boosting and deep learning, the systematic integration of governance standards and compliance is comparatively underdeveloped. The central bibliometric insight, therefore, is that the field has largely converged on methodological excellence but has yet to fully reconcile algorithmic innovation with regulatory legitimacy. This unresolved tension defines a clear trajectory for future research at the intersection of AI, banking risk management, and compliance.

The findings generate several implications. For researchers, the results highlight the need to integrate machine learning techniques with institutional and regulatory frameworks, particularly in the areas of explainability and governance. For regulators, the bibliometric evidence suggests that AI adoption in banking is advancing faster than the development of compliance-oriented research, indicating the importance of regulatory frameworks addressing model transparency, fairness and accountability. For practitioners, the results emphasize the growing relevance of explainable AI and model governance in real-world banking applications, particularly in credit risk modeling and fraud detection.

5.2 Thematic and geographical implications

The thematic structure confirms that the field is organized around a strong AI and machine learning core, with fraud detection and banking-related research (G21) positioned as motor themes. Artificial intelligence, machine learning, and banking function as basic but highly central pillars, indicating that the literature is methodologically consolidated around predictive modeling in financial contexts. At the same time, natural language processing, textual analysis, and explainable AI (XAI) appear as either niche or structurally emerging themes, suggesting a gradual shift toward unstructured data analytics and interpretability. The relative repositioning of bankruptcy prediction and risk toward lower-density areas indicates a transition from traditional statistical dominance toward AI-enhanced extensions rather than a decline in conceptual relevance.

Importantly, the thematic patterns are highly consistent across Scopus and Web of Science, demonstrating structural convergence between the two databases. Both datasets identify similar core themes, similar motor topics, and comparable maturity levels of subfields, reinforcing the robustness of the bibliometric findings.

From a geographical perspective, the collaboration networks reveal a clear concentration of research output in a limited number of leading countries. The United States, China, and the United Kingdom form the central hubs of international collaboration, with dense co-authorship ties extending toward Europe, Asia, and the Middle East. India also emerges as a structurally

important connector within the global network. The dominance of these countries is further confirmed by publication counts, where China, India and the United States lead in total output, followed by the United Kingdom and other European countries.

The comparison between SCP and MCP indicates that leading countries combine strong domestic production with substantial international collaboration. While China shows high single-country productivity, the United States and the United Kingdom display stronger international integration through multiple-country publications. These patterns are largely mirrored in both Scopus and Web of Science datasets, again underscoring database similarity and the stability of geographical findings.

The thematic and geographical evidence suggests a methodologically mature and globally interconnected field, dominated by major research countires and centered on AI-driven financial risk modeling. However, the concentration of influence in a limited number of countries also implies potential asymmetries in knowledge production and agenda-setting within the domain of AI, banking risk, and financial regulation.

5.3 Research gaps and future directions

The comparative analysis of Scopus and Web of Science reveals a high degree of structural similarity, particularly in identifying the intellectual academic core of the field. Both databases consistently highlight the dominance of AI- and machine learning, and the growing importance of fraud detection and trust. Subtle differences between the two databases reveal important research gaps. Scopus tends to capture a broader range of conference proceeding, resulting in slightly stronger visibility. In contrast, Web of Science shows relatively stronger representation of established journals and theoretically oriented contributions. These variations suggest that innovation dynamics and institutional consolidation coexist but are not always fully integrated.

Across both databases, a central gap concerns the limited integration of governance and regulatory compliance into AI-driven research. While predictive accuracy and algorithmic optimization dominate the literature, fewer studies systematically address documentation standards, auditability, fairness, explainability under regulatory scrutiny, and operational deployment in banking environments. Themes such as explainable AI (XAI), trust, and bank risk appear structurally present but not yet fully developed as motor themes, indicating an ongoing transition rather than full consolidation. A second gap relates to the imbalance between methodological sophistication and economic interpretability. The bibliometric patterns suggest that performance metrics remain dominant over institutional applicability.

Geographically, both databases show strong concentration in a small number of countries, primarily the United States, China, India and the United Kingdom, while emerging countries participate mainly through collaboration networks rather than agenda-setting roles. Future research could therefore explore cross-regional regulatory differences, data availability asymmetries, and the impact of institutional environments on AI model deployment.

Looking forward, future directions should prioritize:

- integration of AI models with regulatory compliance frameworks (e.g., explainability, fairness, model governance)
- deeper incorporation of unstructured data (NLP, textual analytics) into risk modeling
- interdisciplinary research bridging machine learning, financial regulation, and institutional economics

While Scopus and Web of Science demonstrate strong convergence in identifying the field's methodological backbone, their differences highlight the need to bridge technological innovation with institutional legitimacy. Future research should move beyond predictive optimization toward compliance, transparency, and governance aligned AI systems in banking and risk management.

6 Conclusions

Digital transformation has rapidly reshaped financial services, making AI-enabled fintech a central theme in both academic research and policy debates (Jia & Liu, 2024; Thottoli et al., 2023). Against this backdrop, this study provides a comparative bibliometric analysis of AI, financial institutions, and risk management research (2011–2025) using Scopus and Web of Science to mitigate the limitations of single-database designs and short time horizons common in prior work (Huda et al., 2026; Saputri et al., 2025). Results confirm a sharp post-2017 growth in scientific output and reveal a stable intellectual academic core across both databases, anchored in foundational contributions on bankruptcy prediction, credit scoring, and modern machine-learning methods. While Scopus and WoS converge strongly in identifying dominant themes and leading research hubs, they also offer complementary perspectives. For example, Scopus provides broader coverage of applied and technical contributions, whereas WoS emphasizes more established, citation-intensive outputs. Overall, the field is methodologically mature yet institutionally fragmented, with a clear need to better integrate governance, explainability, and compliance-grade integration into AI-driven banking and risk management. Future research should therefore move beyond predictive optimization toward transparent, standardized, and regulation-aligned AI systems that can support both scholarly advancement and practical implementation in financial institutions

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Part II: Digital Divide, Regulation and Governance

Combating the Digital Divide: European Regulatory Instruments to Establish a Social and Informed Right of Access to the Internet and Users' Right to Choose Information

Original scientific paper

Francesco Gaspari[1], Giuseppina Agata Di Guardo[2]

ABSTRACT

This contribution outlines the contours of the right of access to the Internet as an informed and social right. The analysis provides a theoretical approach to the most recent European regulatory and policy frameworks, with a close look at the most authoritative doctrinal trends in the areas of fair access to the Internet and the digital infrastructure. Recent EU regulatory initiatives (in particular the Digital Services Act and the European Media Freedom Act) are examined from the perspective of citizens'/users' rights within digital platforms, with a focus on regulatory instruments that maintain effective information pluralism and enable citizens/users to exercise their right to choose informed content. This involves taking effective measures to combat the digital divide, in view of the challenges posed by algorithms and artificial intelligence. In particular, the first part of the paper focuses on the role and pitfalls of digital platforms in the context of the Digital Services Act and the European Media Freedom Act, as well as the related user rights. The second part focuses on the right of access to the Internet, its constitutional and social implications, and the need to combat phenomena that cause digital exclusion, such as the digital divide. Finally, the paper discusses the role of European regulation in establishing a secure, pluralistic European digital space. The analysis concludes that there is a need to expand the forms of protection for EU users/citizens in order to improve information pluralism and enhance their freedom to make informed choices regarding content by putting forward some proposals for addressing and managing the new challenges posed also by AI.

1 *Associate Professor of Administrative Law, Guglielmo Marconi University, School of Law, Via Plinio 44, 00193, Rome, Italy. Scientific affiliations: Italian Association of European Scholars (AIGE); Italian Association of the European Union Law Scholars (AISDUE). E-mail: f.gaspari@unimarconi.it.*

2 *PhD at the Guglielmo Marconi University, School of Law, Via Plinio 44, 00193, Rome, Italy; Formerly Visiting Researcher at the International Institute of Air and Space Law, Leiden University and at the Universidad del País Vasco; Lawyer at the Presidency of the Sicilian Regional Government; E-mail: agatadiguardo@gmail.com.*

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***JEL classification**: K23, K24, K15, K33*

1 The role of the European Commission in creating the European Digital Space

The Commission has recently taken on a key role in European digital governance, a strategic sector of central importance for the future of Europe and its citizens (European Commission, 2015). In particular, the dual objective pursued by the Commission (Ferri, 2022a; Ferri, 2022b: p. 277 ff.) is, on the one hand, to build a European digital single market that is truly strong and competitive on a global scale and, on the other, to promote, by including in the digital environment, the fundamental values and rights that are an integral and indispensable part of the European legal system, of which the right of access to the Internet is a fundamental prerequisite. Moreover, from a regulatory point of view, the Commission has the power conferred on it by Article 17(1) TEU to '*promote the general interest of the Union*', a broad and deliberately vague formula that leaves ample room for manoeuvre in pursuing its institutional mission[3]. Furthermore, the Commission has the power to set the European political agenda, identifying the objectives that deserve attention at supranational level and on which policymakers are called upon to act. It also plays a crucial role in defining and developing European policies in line with the objectives identified. More specifically with regard to digital technologies, it has been clear since the beginning of the new millennium that they would revolutionise the world at an unprecedented speed, profoundly influencing the way we communicate, work, and live, and transforming society, the economy and work. Digital technology has therefore become a top priority on the European political agenda, and various actions have been taken in the attempt to reduce the gap between the EU and its competitors on the world stage, as well as to achieve the ambitious goal of 'digital sovereignty'.[4]

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3 *For an examination of the role played by the Commission in the European landscape, see Gianfrancesco, 2012: 1 ff. For a commentary on Article 17 TEU, see the appropriately adapted English version of the contribution in Blanke and Mangiameli, 2013.*

4 *Since the Tallinn Summit in 2017, Heads of State and Government have expressed their intention to exploit the opportunities offered by new technologies while managing the risks that the digital revolution threatens to pose to individuals and society as a whole. See press release, Tallinn Digital Summit 29 September 2017, available at: www.consilium.europa.eu. Continuing in the direction set by the Tallinn Summit and expanding on this initial statement of intent, the Commission has made the creation of a secure, open digital space that respects fundamental rights and the values of the Union a top priority for the five-year period 2019-2024. See Realising Europe's Digital Decade, 21 June 2024, available at: www.ec.europa.eu. In relation to the expression 'digital sovereignty', it has found terms in EU institutional documents that are not perfectly comparable, such as 'technological*

Despite doubts about the real meaning of this expression, it is clear that the term has a more political than legal meaning (as recognised by Finocchiaro, 2022: p. 811). For the Commission, achieving digital sovereignty means, first and foremost, gaining strategic autonomy in the digital field, reducing the Union's technological and economic dependence on other countries, primarily China and the United States. Furthermore, the reference to digital sovereignty has made it possible to strengthen European (internal) sovereignty with respect to Member States in a sector of absolute strategic importance, limiting or even removing the regulatory power of national legislators in this area (Allegri, 2021: p. 2). Article 114 TFEU provided the legal basis for the adoption of the Digital Market Act, the Digital Services Act and the Artificial Intelligence Act, as it is the cornerstone for the harmonisation/approximation of laws for the establishment and functioning of the internal market (on the constraints of this legal basis, see Eifert, Metzger, Schweitzer, and Wagner, 2021: p. 1000-1001).[5]

This has led to a proliferation of communications (European Commission, 2020a, 2020b, 2020c, 2020d), action plans[6] and strategies[7] which have gradually contributed to building the value base[8] and the reference framework within which more specific proposals for action have subsequently been developed.

In this sense, the copious literature on European digital governance has often referred to the term 'digital constitutionalism' (on the subject of digital constitutionalism, see Gill, Redeker, and Gasser, 2015; Celeste, 2019: p. 76 ff.; De Gregorio, 2020: p. 41 ff.; Pollicino, 2023: p. 569 ff.; De Gregorio and Pollicino, 2021. For a critical reading of digital constitutionalism, see Golia, 2023: p. 1-31). Although this expression has never entered the European political and institutional discourse and lexicon[9], the EU's intervention in digital matters seems to evoke the dual vocation of modern constitutionalism[10]: on the

sovereignty' and 'digital autonomy'. On the subject of digital sovereignty, see Floridi, 2020: p. 369 ff.; Roberts, Cowls, Casolari, Morley, Taddeo, Floridi, 2021: p. 1 ff.; Finocchiaro, 2022: p. 809 ff.

5 *For the sake of completeness, it should be noted here that the legal basis for the AIA is supplemented by Article 16 TFEU (see Recital 3, AIA).*

6 *European Commission, 2025g; European Commission, 2020e, which includes the DSA among its main implementation tools.*

7 *The Union's digital strategy also includes the European data strategy, the European industrial strategy and the European cybersecurity strategy.*

8 *See HLEG, Ethical Guidelines for Trustworthy Artificial Intelligence, 2019. Following on from the Berlin Declaration on the Digital Society and Value-Based Digital Government and the Lisbon Declaration on Digital Democracy, the Commission presented the European Declaration on Digital Rights and Principles for the Digital Decade on 15 December 2022.*

9 *On the lack of a single definition of 'European constitutionalism' and of unanimity of views in doctrine regarding its very existence, see Massa, 2022.*

10 *In this regard, see Article 16 of the Declaration of the Rights of Man and of the Citizen of 26 August 1789. Pollicino (2023) emphasises this dual nature with reference*

one hand, to protect the fundamental rights of citizens; on the other, to act as a limit on powers and a source of rebalancing between them.

In the digital society, however, the original vocation of constitutionalism to represent a limit on (state) power is interpreted as a form of limitation on the exercise of private power (Conti, De Stefano, & Pollicino, 2021, states that "*The variable geometry of power is followed by the equally variable geometry of constitutionalism*"; Torchia, 2024: p. 14 ff.). This refers, in particular, to the power acquired in recent years by large technology companies operating in the digital market, an oligopolistic market with a high degree of concentration, few operators and a low degree of contestability, as has been authoritatively described (see Torchia, 2024: p. 67). These characteristics have allowed a few companies to acquire immense digital power, which has quickly transformed into economic power, eventually taking on 'para-public' significance (Pollicino, 2023: p. 570. See also Floridi, 2020, which addresses the issue of the conflict for digital sovereignty in the relationship between states and technology companies)[11], affecting not only the economy, but also relationships between individuals and between individuals and public authorities[12].

The impact of *BigTech* therefore affects the most intimate dimension of the Union, its very identity and the essential values of the integration process enshrined in Article 2 TEU, such as human dignity, democracy, the rule of law and respect for fundamental rights.

Therefore, the problems and opportunities that technology poses in the 21st century cannot be ignored by constitutionalists and regulators. On the contrary, the main challenge facing them is precisely that of preserving the protection of fundamental individual rights in the context of the digital revolution, through the development of an effective regulatory framework (on the role of constitutionalism in the digital age see Frosini, 2020: p. 465; Celeste, 2019; and on the prospects for digital constitutionalism in Europe, see De Gregorio, 2022).

However, the complexity of regulating the digital world and technological progress, partly due to the rapid pace of innovation and the interdisciplinary nature of creating rules that are sustainable from both a legal and technological point of view, is reflected in the slowness of law-making processes in these areas. Indeed, the limited regulatory capacity of public authorities in the digital ecosystem stems (or stemmed), on the one hand, from a marked information asymmetry, due to continuous and rapid technological innovation, which leads public entities to a partial and delayed understanding of the dynamics of digital markets and, on the other, the internal technical functioning of platforms and algorithms.

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to digital constitutionalism, referring to the process of European regulation of the digital economy as a 'first embryo of a European digital constitution'.

11 *On the subject of private powers, see Han, 2023; Ferrarese, 2022; Zuboff, 2019.*

12 *Consider the circulation of fake news, the political profiling of individuals and the bias of the information to which users consequently have access, and how these affect citizens' opinions, public debate and, ultimately, democracy. See Candido, 2020; Magnani, 2018.*

Furthermore, the force of public rules, which tend to be limited to the national territory, has always clashed with the global dimension of large digital platforms. This makes it difficult for national institutions both to obtain the information needed to compensate for the exiting information asymmetry and to define rules that are effective in terms of results, as such rules apply only to a small subset of the platforms' total actions and users.

This is why the European Commission, thanks to its expertise, has presented itself as the actor capable of formulating legislative initiatives in this crucial sector in the most effective way. In the Commission's view, the provision of clear and uniform rules would increase the confidence of operators and users in the European digital space, thereby enhancing the attractiveness of the Union in a global context. Hence, it is not surprising that the Commission opted to adopt regulations under Article 288(2) TFEU[13], demonstrating a particularly incisive attitude compared to its competitors[14]. Furthermore, given the irrelevance of national borders in the online world, as was already the case with the General Data Protection Regulation (GDPR, Reg. 2016/679), the Commission has proposed an 'extraterritorial application' of the regulations (Floridi, 2021, p. 215 ff. who refers to the '*aterritorial*' application of the regulation). The above guidelines permeate the entire regulatory framework comprising the so-called digital package, which includes the Digital Markets Act (DMA, Reg. 2022/1925) and the Digital Services Act (DSA, Reg. 2022/2065), and the Artificial Intelligence Act (AIA, Reg. 2024/1689).

The decision to issue incisive and uniform regulations was driven by the recognition of an intrinsic weakness in the self-regulation or co-regulation approach solutions adopted by the digital platforms themselves, in which the major global players and network powers defined the rules for managing their own economic activities[15]. The new rules therefore apply to entities which, regardless of their place of establishment, provide services or carry out activities for EU citizens[16]. In this way, the scope of European rules is strengthened, spreading their effectiveness beyond European borders through

13 *Although the three acts remain formally regulations, they have been identified as 'Acts' by the Commission. According to Eifert, Metzger, Schweitzer, and Wagner, 2021: p. 989, this demonstrates the Commission's desire to define a framework for the digital economy that aims to set global standards, not limited to the European sphere.*

14 *The Union has opted for an alternative path to both the private self-regulation model promoted by the United States and the state-centric, government-led model supported by authoritarian regimes (Russia and China). On this point, see Chiti and Marchetti, 2020: p. 29 ff.*

15 *The contractual rules between users and large platforms, voluntarily accepted by the former by signing the terms and conditions of service, have become rules for the management and governance of interactions within communities made up of huge groups of users. In the context of pervasive market and contractual power, platforms have always had the real possibility of unilaterally establishing their own terms of service, as general terms and conditions of contract that have come to constitute what has been defined as platform law.*

16 *See Art. 1 DMA; Art. 2 DSA; Art. 2 AIA.*

the well-known Brussels Effect (Bradford, 2020)[17].

Moreover, in order to ensure the right balance between protecting rights and supporting the market, the Commission has proposed a risk-based approach in both the DSA and the AIA. The latter is a regulatory model that allows for differentiated obligations depending on the different levels of risk potentially posed — by AI systems or digital system providers — to fundamental rights (On the risk-based approach, see De Gregorio and Dunn, 2022: p. 473 ff.; Tommasi, 2023: p. 279 ff.). The risk-based approach aims to ensure the proportionality of regulatory intervention, adequately protecting end users while avoiding stifling the dynamism of the digital sector.

2 The role and pitfalls of digital platforms in terms of media pluralism: New user rights in the light of the Digital Services Act (DSA) and the European Media Freedom Act (EMFA)

The regulatory approach taken by the DSA, as we shall see, is evident from the impact of platforms, especially those managed by *Big Tech*, on user/consumer rights. Over time they have these platforms have acquired such economic power that they influence global markets and competitive dynamics due to other specific aspects of the platform economy, which have to do with data and the efficiency of algorithms (see Manganelli and Nicita, 2022).

The activity of large digital platforms is focused, on the one hand, on the collection of user data (which, in the case of platforms based mainly on advertising, such as Meta and Google, are implicitly exchanged for free services) and, on the other, on its use on the different side of a two-layered market, in which the valorisation and monetisation of data depends on the ability of platforms to profile users. In other words, through massive and sophisticated profiling, platforms can understand every user's willingness to pay for each kind of good or service advertised, brokered or directly sold, and implement (almost) perfect price discrimination, thus appropriating (nearly) all consumer *surplus*. In other words, large digital platforms are able to redistribute consumer welfare to their advantage, as is the case with 'traditional' monopolies, but unlike the latter, platforms lead the market to efficient configurations.

Indeed, the spread of online platforms and, above all, social networks, has produced an epoch-making transformation of the information system. In the online information system, there is a much wider availability of content, both informative and non-informative, including self-produced content, which comes from a broad and eclectic universe of sources. Therefore, on the Internet, freedom of expression and freedom of information are no longer limited by the scarcity of resources, which is a major constraint for traditional media. This

17 *For large technology companies, it tends to be less expensive to comply with European rules than to abandon the European market. In terms, Torchia, 2024: p. 27. With regard to the impact of the European digital market on countries bordering the Union, see Nyman-Metcalf and Papageorgiou, 2018: p. 7 ff.*

has been considered by many to be the ideal world of free information and freedom of speech, as a result of competition between multiple alternative sources in the 'free market of ideas'.[18]

In the information and media system, the Italian Constitutional Court has recognised a functional link between the passive aspect of freedom of expression, the right to information, and pluralism of information, where "*pluralism manifests itself in the concrete possibility for all citizens to choose between a multiplicity of information sources*"[19]. In its known case law, the Court distinguishes between the concepts of internal pluralism (or pluralism within the source) and external pluralism (or pluralism of sources), referring them, respectively, to the specific function exercised by the public broadcaster and to contexts in which a plurality of media (publicly or privately owned) can operate in conditions of competition in the market, in order to "*promote access to the radio and television system for the greatest possible number of different voices*."[20] In a context such as the digital one, where the traditional elements of scarcity of supply (such as, for example, frequencies and the need for substantial funds to disseminate information) no longer apply, one might be led to believe that external pluralism is sufficient to guarantee a real choice among a variety of information sources for all citizens. However, the information ecosystem offered by the Internet has additional characteristics, inherent in the relationship between competition and pluralism, which differentiate it from the old media and create new scarcities and new '*market failures of ideas*' (Nicita, 2021; Pollicino, 2017).

As is well known, due to a lack of constraints and very low transaction costs on the supply side, a tangible risk of the online information system is, paradoxically, 'information overload', as a result of which the individual's freedom of choice among information sources is no longer limited by supply capacity, but by the user's own ability to select sources in an environment of excessive 'noise'. In this context, algorithmic information sources (such as news aggregators, search engines and social networks) address and solve the problem by efficiently selecting relevant information and responding to consumer preferences for information content. However, in order to do this, algorithmic selection reduces the user's scope for awareness and (explicit) choice. In the digital marketplace of ideas, choice is reduced to what the platform, as the gatekeeper to information, proposes.

On the one hand, therefore, each user reveals to the algorithms what they are interested in receiving and, on the other, they are driven by the same algorithms to know only what seems to interest them. What the platform offers is in fact what the user (already) prefers, their existing worldview, which they have revealed to the platform, helping to create and amplify the notorious

18 *The well-known doctrine of the 'free marketplace of ideas', developed most comprehensively by Justice J. Holmes more than a century ago in Abrams v. United States, 250 U.S. 616 (1919).*

19 *See Constitutional Court, Judgment No. 826 of 1988.*

20 *Constitutional Court, Judgment No. 112 of 1993.*

'digital echo chambers'.[21]

If the result of algorithmic selection by large platforms is 'information capture', then, when the commodity offered is information, this outcome inevitably undermines pluralism, both in terms of choice and in terms of exposure diversity. The efficiency of the algorithms in satisfying user preferences (and consequently in maximising platform profit) allows consumers to receive only the information that adheres to their existing representation of the world (Helberger, Karpinnen & D'Acunto, 2016; p. 191–207; Parcu, Brogi, Verza, et al., 2022). Information pluralism, however, primarily implies that individuals be potentially exposed to information content with which they may currently disagree, but on which they must still have the possibility of making a choice – one that remains reversible over time. The user could certainly change platforms, i.e. find a different gateway to information, but — assuming they have incentives to do so — this choice would still not be able to restore effective pluralism in terms of both choice and exposure to diversity.

As described, the main obstacle to competition in platform service markets, including social networks, in addition to network effects, is the availability of the information assets constituted by user data. Effective competition can only develop if and to the extent that alternative platforms acquire information assets similar to those of the gatekeepers.[22] Therefore, the development of the digital economy and platforms acting as gatekeepers raise new questions for the legal regulation of the market. Economies of scale, network externalities (the more users there are, the greater the value of the platform for them) and the plurality of services offered allow the formation of enveloping 'digital ecosystems'. Market power thus penetrates people's lives without any visible coercion, indeed with their consent, because the efficiency of the service pushes individuals to accept the terms of use without considering the effects of tracking carried out through the exploitation of the data generated. If and when this happens, any new platform chosen by the user will be equipped with the necessary information assets and will operate through an algorithmic selection of content, once again providing the user with what they prefer, i.e., in all likelihood, the same content that the original platform would have offered — or would continue to offer in the case of multihoming. Hence, the user's choice will continue to be restricted to a very small 'targeted' subset

21 *There have always been phenomena of subjective self-limitation of information sources, i.e. those who choose to adhere unconditionally to information from one or a few sources (such as buying only one partisan newspaper or obtaining information only from a party headquarters). However, it is precisely the awareness of the choice and its (albeit costly) reversibility that greatly differentiates these areas from those of digital echo chambers, where there is no conscious choice of self-limitation: this is imposed by the algorithmic selection and business model of respective platforms.*

22 *Given the economic characteristics of digital markets, this outcome is more likely to be the result of regulatory action than market dynamics, including through data portability, whereby users can transfer the information collected by one platform to another platform - Article 6(9) of the DMA and Article 20 of the GDPR. See Manganelli, 2022: p. 93-131.*

(corresponding to the profiling of that same user) of everything that is present on the platform on the supply side. This is the 'privacy paradox': by processing data collected in multiple markets, large platforms make increasingly reliable predictions about user preferences, which is fundamental, among other things, for the personalised advertising market, with benefits for small businesses, as individual needs are met with ever greater precision, thus saving time.

The lack of interest in privacy policies among most consumers would therefore have a rational basis (Cofone, 2015; Marthews & Tucker, 2019; Carr, 2019).[23] The more extensive and efficient the ecosystem becomes, the less reason consumers have to seek alternatives. In this context, however, anti-competitive outcomes may arise, with a reduction in the quality of services offered and the exclusion of competitors due to the blocking effect caused by network externalities. It remains to be seen whether this is balanced by efficiency gains. For this reason, regulation aimed at increasing the contestability of digital markets and reducing the costs of change for users, which can resolve competition issues on goods and services other than information, does not seem sufficient to solve the problems of pluralism in an algorithmic online information environment.

Consequently, in order to protect the right to be informed online, it seems necessary to focus primarily on internal pluralism, in a new and different sense: internal pluralism on the side of individual demand for information and not (only) on the side of generalised supply to all users. It is on the demand side that the new elements of scarcity lie: the user's time and attention. Thus, it is necessary to aim to improve the awareness and tools available to users in selecting content. It is on this side that the algorithmic selection of content takes place and it is on this side that each user's freedom of choice is primarily restricted. It is, in fact, on the individual demand side that distortions in algorithmic selection occur, further restricting the user's freedom of choice.

As is well known, the business model of social networks (as well as other platform services) allows anyone who pays to promote their content on the platform in order to reach certain categories of users. This paid free reach on the supply side alters the 'organic selection' of algorithms based on user preferences[24], highlighting the great prominence and imbalance of the right (and power) to inform, on the part of those who have the economic resources to do so, compared to both those who do not have such resources and the right to be informed.

Once again, the information and transparency obligations in relation to the fact that content is sponsored (or that a payment has altered the

23 *On economies of scope in data aggregation, Duch-Brown, Martens, Mueller-Langer, 2017. On the production of data, replicable and non-consumable, so that there would be no limits to users' expenditure capacity, Zeno Zencovich, 2018: p. 1, and 8 ff. On behavioural conditioning caused by partial or opaque information on terms of service, Acquisti, Taylor, Wagman, 2016: p. 442-492.*

24 *A distinction is made between 'organic selection', in which the content offered is based on user preferences, and 'non-organic' selection, where the result is influenced by a payment aimed at giving greater visibility.*

aforementioned 'organic selection' of content), as required, for example, by the 2019 amendments to the Unfair Commercial Practices Directive[25], may be sufficient to reintroduce informed choice for services and products other than information, but do not seem capable of having a decisive impact on information pluralism. In this context, in order to restore pluralism, understood as the 'organic selection' of information assets, it seems necessary that algorithmic selection should not be exclusively geared towards maximising platform profits (including by satisfying user preferences), but should make it possible to expand or modify user preferences over time, in order to reintroduce effective freedom of choice among a variety of alternative sources. In other words, it would be essential to create margins of choice on the functioning of the selective mechanisms of algorithms, at least at the meta-choice level, for example by allowing users to choose whether and to what extent they want to be exposed to content that differs from their revealed preferences. In essence, users should be able to express meta-preferences on how the algorithm reacts to their revealed micro-preferences and, of course, on how much they want to be exposed to the free reach of sponsored information content.[26] Therefore, it is not a question of intervening in the regulation of content itself, but rather in the way it is reached, restoring the user's freedom (and power) to decide what they want to be reached by.

This pro-pluralism intervention, acting on the demand side with consumer empowerment modules, does not require an explicit definition of social network platforms as audio-visual media service providers (an issue that is evolving at the regulatory level (Manetti, 2023: p. 525 ff.; Meroni & Brogi, 2021), but is still controversial). Such a change would certainly entail costs for the platform in terms of lower advertising revenue, fewer interactions between users, less data exchanged, less information captured, and therefore a greater possibility of users leaving the platform; however, it seems a necessary remedy if effective online information pluralism is to be restored. Article 38 of the Digital Services Act (DSA) on recommendation systems goes partly in this direction.[27] This provision stipulates that, in addition to the transparency requirements to which all online platforms are subject (Article 27 DSA), very large online platform providers must ensure that users have at least one option for each of their recommendation systems that is not based on profiling.

In addition, very large online platforms, identified according to a quantitative

25 *Directive 2005/29/EC on unfair commercial practices, amended by Directive (EU) 2019/2161 for better enforcement and modernisation of Union consumer protection rules.*

26 *Obviously, this does not apply to being subjected to advertising (unless as an alternative to paying a subscription fee, as is the case with YouTube Premium, for example), otherwise the advertising-based business model would be unsustainably undermined.*

27 *A recommendation system is a "fully or partially automated system that an online platform uses to suggest specific information, via its online interface, to recipients of the service or to prioritise such information, including as a result of a search initiated by the recipient of the service or by otherwise determining the relative order or importance of the information displayed" (DSA Art. 3(s)).*

parameter (average monthly active users of the service in the Union equal to or greater than 45 million), are required to conduct an assessment of the systemic risks caused by or related to the operation and use of their services and to take reasonable and effective measures to mitigate those risks, as well as to undergo an external and independent audit. With regard to compliance with their respective obligations by these online platforms, the regulation provides for new supervisory and sanctioning powers for the European Commission.[28]

Moreover, the rapid advancement of technology affects the rules and principles that govern the suppression of market abuses and unfair practices that harm consumers. It also affects the imposition of ex ante transparency obligations on digital companies and online platforms. To illustrate this point, consider web interfaces and, more generally, the 'graphic' architecture of platforms where commercial transactions take place (on this topic see Ciancimino, 2024: p. 803 ff.). Referring to recital No 67 of the Regulation no 2022/2065/EU (the Digital Services Act), one can see that:

> Providers of online platforms should therefore be prohibited from deceiving or nudging recipients of the service and from distorting or impairing the autonomy, decision-making, or choice of the recipients of the service via the structure, design or functionalities of an online interface or a part thereof. This should include, but not be limited to, exploitative design choices to direct the recipient to actions that benefit the provider of online platforms, but which may not be in the recipients' interests, presenting choices in a non-neutral manner, such as giving more prominence to certain choices through visual, auditory, or other components, when asking the recipient of the service for a decision.

It should be emphasised that the logic underlying the aforementioned prohibition goes beyond the already existing prohibition of unfair commercial practices: Article 25 of the same Digital Services Act, dedicated in particular to the 'design and organisation of online interfaces', provides that "*Providers of online platforms shall not design, organise or operate their online interfaces in a way that deceives or manipulates the recipients of their service or in a way that otherwise materially distorts or impairs the ability of the recipients of their service to make free and informed decisions*", even when such activities do not necessarily constitute unfair commercial practices within the meaning of Directive 2005/29/EC (Article 25(2) DSA). All of this confirms the existence of a digital vulnerability among web and platform users, which is a relevant issue that should be taken seriously.

In fact, the functioning of the online interface does not always and in all cases introduce a 'false reality' and the consequent classification of the practice as unfair; however, it must be prohibited nonetheless, since it can easily induce the user, especially if identified as particularly vulnerable, to behave or act in a certain way. After all, the conditioning of the will and the exploitation of vulnerabilities affect not so much the conscious part of the person, inducing them to make a mistake, but rather the subconscious: in the digital environment,

28 *Compare the articles in Section 4 of Chapter III of the Regulation.*

the exploitation of vulnerabilities acts not so much on the conscious part of the individual, but rather on the unconscious hidden behind the conscious space (Vettori, 2024: p. 331).

Furthermore, it should be remembered that targeted advertising is not prohibited tout court, but is subject to a set of rules aimed at preventing the exploitation of iternet users. Thus, article 26 of the Digital Services Act states that platform providers displaying advertising on their online interfaces shall ensure that, for each individual advertisement presented to each individual recipient, the recipients of the service are able to identify in a clear and unambiguous manner and in real time a number of elements, comprising "*that the information constitutes advertising, including through visible markings*". Moreover, recital 68 then specifies that platforms "*should ensure that the information is salient, including through standardised visual or audio marks, clearly identifiable and unambiguous for the average recipient of the service, and should be adapted to the nature of the individual service's online interface*". Even more interesting, as it could provide for greater gradation and therefore freedom of choice, is the provision in article 20 of the European Media Freedom Act (EMFA) concerning the right to personalise audio-visual media services.

Although this provision was designed for reception device interfaces (remote controls), Article 20 could be interpreted broadly, in the sense described above, and give users of large digital platforms the right "*to easily change the configuration, including default settings, of any device or user interface controlling or managing access to and the use of media services providing programmes in order to customise the media offering in accordance with their interests or preferences in compliance with Union law*".

This broad interpretation could also be linked to one of the self-regulatory commitments set out in the Enhanced Code of Practice on Disinformation of 2022, and in particular measure 2 of commitment 19, which requires relevant signatories (including Facebook, Instagram and Twitter) to provide service recipients with the ability to select and modify their preferred options for relevant recommendation systems at any time, providing users with transparency on these options.

Moreover, adjustments in this regard could come from the platforms themselves with the implementation of articles 34 and 35 of the DSA, which require very large online platforms to assess and mitigate the systemic risks arising from the operation of their service, including algorithmic systems, which may generate current or foreseeable negative effects on the exercise of the fundamental rights of freedom of expression and information, including media freedom and pluralism.

Finally, in line with this basic vision, article 3 of the EMFA Regulation[29] provides in general that "*Member States shall respect the right of recipients of media services to have access to a plurality of editorially independent media content and ensure that framework conditions are in place in line with this Regulation to safeguard that right, to the benefit of free and democratic discourse*". In this

29 *Article 3 EMFA - Right of recipients of media services.*

regard, information pluralism seems likely to extend beyond the boundaries of media services as traditionally understood, to encompass both video-sharing platform providers and very large online platforms.

From this brief overview, it is clear that the imposition of transparency and information requirements on the functioning of algorithms and recommendation systems, such as those prescribed by the DSA (Article 27), are necessary tools for consumer-user protection, but are not sufficient in most circumstances to restore true freedom of choice, due to the 'information capture' described above.

However, it is also true that the DSA is permeated by a protective logic, which undoubtedly has a preventive rather than a repressive function. For example, the aforementioned Article 25 of the Digital Services Act states that the platform must meet certain requirements regarding the structure, design or functionality of an online interface. These requirements can only concern the obligation to care for and protect the user, beyond the transparency of the commercial operation and regardless of whether there is a contractual relationship.30 In particular, looking at the relationship between users and providers of digital spaces in which the former operate, protection obligations impose a series of specific measures on the latter for the benefit of the former. These measures range from targeted communication obligations and assistance in forming free consent, to preventing possible manipulation or discrimination by third parties.

3 The right of access to the Internet and its constitutional and social implications for effectively combating the digital divide

The Internet, understood as a place of maximum individual freedom transcending states (for further information, see Bassini, 2019), certainly represents an opportunity to improve forms of democracy, especially in terms of political participation. It is, in fact, a tool that enhances individual freedom, which is expressed through the potential of so-called *net freedom*, particularly in terms of freedom of expression, which can now be exercised in ways that were never possible before. Today, thanks to the Internet, it is truly possible to seek, receive and disseminate information and ideas without regard to borders. This is a considerable achievement in terms of individual freedom (see Frosini, 2015). Therefore, the Internet and technology in general represent a development and enhancement of freedoms.

Authoritative doctrine has argued that in a liberal constitutional state, "*political policy should always be directed towards measures that enhance and increase individual freedoms, and the use of technology can only be instrumental to this objective*" (Frosini, 2017: p. 658).

A prerequisite for the successful participation of citizens through the use of

30 *Reasoning in this way, the obligatory relationship is enriched with a protective function that extends beyond obligations in the classical sense (with a service as its object) to a relational responsibility, according to Nicolussi, 2024: p. 1076.*

the Internet (netizenship, a portmanteau of net and citizenship) is the right of access to the Internet. Access to the Internet is the means by which individuals interact with public authorities and thus exercise their rights of citizenship. Denying access to the Internet, or making it expensive and therefore exclusive, means precluding the exercise of most citizenship rights.

The Internet can therefore serve, in a positive way, to increase the level of political participation of citizens, through the pluralism of information and the exchange of information between citizens and between them and the representatives of institutions and administrations. It has already changed the perception of democracy and public opinion, correcting the way in which both judgements and expectations are formed, because citizens tend to become more demanding of their governments, strengthening the powers of control of voters over elected representatives.

However, we must not forget that on the Internet we are faced with a complex network of actors, especially providers and platforms, which are often economic operators of global importance, with financial resources greater than those of many medium-sized states. Through hidden profiling and discrete forms of surveillance, they have accumulated an unimaginable amount of information and data, enabling them to influence individuals' needs, desires and their inclinations (including political ones) (see Michetti, 2023), as well as to exercise rather pervasive forms of (self-)regulation over the network[31].

Hence, there is an unavoidable demand by the people of the network, directed at private operators and governments, for new regulation of cyberspace in line with a typically constitutional approach, i.e. one referring to the protection of fundamental rights and democracy, as well as other European values (Art. 2 TEU). Such regulation requires the free exercise of freedoms, the prohibition of manipulation of the truth, and the overcoming of surveillance and data accumulation by private operators and governments. Above all, it requires the prohibition of the political use of data. Can digital sovereignty achieve all this?

Respect for democratic rights and principles could certainly be achieved through multi-level legislation and/or multilateral agreements. In this way, if not a (global) constitution for the Internet, at least an *Internet Bill of Rights* could be formalised.[32] In this sense, a projection of constitutionalism onto the Internet raises, first and foremost, the question of regulation, which must be effectively permeated by the principles of the 'rule of law' in the most current and comprehensive sense of the term. In states that embrace these principles, legislation has very often given rise to 'digital citizenship', even if the range of rights and entitlements that this expression may encompass is not always entirely clear. However, it would certainly include the right to access the Internet, the right to digital education, the right to electronic democratic

31 *For a broad reflection on the ability of platforms to regulate the architecture of the network, see Santaniello, 2021.*

32 *According to Rodotà, 2010: p. 343: "The choice of the ancient formula of the Bill of Rights has symbolic power, highlighting that we do not want to limit online freedom but, on the contrary, to maintain the conditions for it to continue to flourish. That is why 'constitutional' guarantees are needed" (our translation).*

participation, to name a few. With regard to the right of access to the Internet, there is no doubt that this is now a genuine social right. Such social rights and 'digital citizenship' may be jeopardized by the digital divide issue. According to Eurostat, the digital divide "refers to the distinction between those who have access to the Internet or other digital technologies and are able to make use of online services, and those who are excluded from these services." (Eurostat, 2023). In a historical era in which most services are provided through the use of platforms and "*more daily tasks are carried out online, from applying for a job to paying taxes or booking tickets, using the Internet has become an integral part of daily life for many Europeans*" (European Commission, 2010a: par. 2.6), the digital literacy matter is of paramount importance.

The rapid and significant development of information and communication technologies has created (or aggravated) discrimination, especially due to age, education, geographical location, social class membership, disabilities, exacerbating phenomena of digital divide (on digital divide see, among others, OECD, 2001; OECD, 2015: p. 123 ff.). In this respect, the EU Commission also points out that "Bridging this digital divide can help members of disadvantaged social groups to participate on a more equal footing in digital society (including services of direct interest to them such as eLearning, eGovernment, eHealth) and to tackle their disadvantage through increased employability." And it is for this reason that "Digital competence is thus one of the eight key competences which are fundamental for individuals in a knowledge-based society." (European Commission, 2010a: par. 2.6).

As the Commission observes, "People's enjoyment of digital technologies, be it as citizens, consumers or workers, is marred by privacy and security concerns, by insufficient internet access, insufficient usability, by lack of relevant skills or by lack of accessibility for all. Europeans are frustrated when ICT do not deliver their promise of better public services." (European Commission, 2010a: par. 1).

In the Flagship Initiative 'A Digital Agenda for Europe', the EU Commission points out the need to "promote internet access and take-up by all European citizens, especially through actions in support of digital literacy and accessibility." (European Commission, 2010b: p. 15-16. See also European Commission, 2010a: par. 2.4).

The aim set by the Commission is to "deliver sustainable economic and social benefits from a Digital Single Market based on fast and ultra-fast internet and interoperable applications, with broadband access for all by 2013, access for all to much higher internet speeds (30 Mbps or above) by 2020, and 50% or more of European households subscribing to internet connections above 100 Mbps." (European Commission, 2010b: p. 15-16. See also European Commission, 2010a: par. 1).

More recently, on 9 March 2021, the EU Commission presented a vision and perspectives for Europe's digital transformation by 2030. The commission proposes a digital compass that develops around four cardinal points: skills, government, infrastructure, and business (European Commission, 2025a).

The fight against digital divide phenomena is at the heart of the European Union's most recent initiatives, among which is the European Declaration on Digital

Rights and Principles (European Parliament, Council, European Commission, 2023), signed by the Presidents of the Commission, the European Parliament, and the Council. Through such a joint Declaration, the European Union "wants to empower people to fully enjoy the opportunities that the digital transition is bringing." (European Commission, 2025b) The Declaration consists of a set of digital rights and principles that reflect EU values and promote a human-centric, secure, and sustainable vision for the digital transformation. Among such rights and principles, a crucial role is played by education and skills, necessary to enjoy the benefits of digital technology. The Commission has committed to regularly monitor the application of digital rights and principles across the EU (on the monitoring report see European Commission, 2025c). Other initiatives have been taken by the EU with the aim to strengthen basic and advanced digital skills, like 'The Union of skills' (European Commission, 2025d), the Action Plan on Basic Skills (European Commission, 2025e), as well as other initiatives outlined by the 2025 monitoring report by the EU Commission (European Commission, 2025f: p. 20 ff.).

These initiatives are based on data on digital literacy in the European Union. In particular, according to data from the EU Commission, "Yet, 150 million Europeans – some 30% - have never used the internet". As the Commission outlined, "This group is largely made up of people aged 65 to 74 years old, people on low incomes, the unemployed and the less educated." (European Commission, 2010a: par. 2.6).

More recent data confirm such a trend. Indeed, the EU Commission data (DESI indicators, 2025) show a significant deficit in digital literacy. In particular, individuals with at least basic digital skills account for 45.75%, below the EU average of 55.56%, Those with above-basic digital skills represent 22.21%, which is likewise below the EU average of 27.32%. By contrast, with regards to digital infrastructure, the data show that Italy covers 99.49%, which is above the EU average of 94.35%.

The 2025 monitoring report on the application of digital rights and principles across the EU presented by the EU Commission provides an overview of action at both EU and national levels to implement commitments in the Declaration, focusing on initiatives adopted by the end of 2024 (European Commission, 2025c). As for digital literacy, almost one third of Europeans (29%) do not feel appropriately equipped for the digital decade. The European Commission reaffirmed the EU commitment to promoting digital education and training (European Commission, 2025f: p. 20).

The issues related to the digital divide are at the centre of the initiatives of the Italian legal system, which, on the one hand, attributes fundamental importance to the profiles of digital computerization and digital skills, planning actions necessary for the pursuit of the objectives relating to the digitalization of the country, including the elimination of the digital divide throughout the peninsula (Sabatini, 2014: p. 24); on the other hand, Article 8 del Digital Administration Code (Legislative Decree No. 82/2005), entitled "Computer literacy of citizens" ("*Alfabetizzazione informatica dei cittadini*"), establishes that the State and other public bodies listed in Article 2, paragraph 2, of the same Code, "promote initiatives aimed at encouraging the spread of digital culture among citizens, with particular attention to minors and categories at

risk of exclusion, also with the aim of encouraging the development of legal IT skills and the use of digital services by public administrations with specific and concrete actions, making use of a range of different means including radio and television services."[33]

More recently, the Italian legislator has adopted other measures aimed at overcoming (or at least mitigating) the problem of reduced digital literacy within the framework of the approval in 2015 of the two national plans: Ultra Broadband and Digital Growth.[34] Even more recently, with the National Recovery and Resilience Plan (PNRR) (on this point see Cocchiara, 2023: p. 189 ff.) and then with Law 23 September 2025, No. 132 (the Italian AI Act), the theme of digital literacy takes on a central role.

Italy is the first European Union country with a national framework aligned with the AI Act (Article 1, paragraph 2, Law No. 132/2025). The Italian legislator is not merely adapting to supranational legislation, but is also redesigning governance, investments, responsibilities and employment relationships, and training. In terms of training, the legislator requires mandatory training for magistrates and other public administration employees. Specifically, for magistrates, Article 15, paragraph 4, assigns the Ministry of Justice the task of promoting educational activities on the topic of artificial intelligence and the use of artificial intelligence systems in judicial activity, aimed at basic and advanced digital training, the acquisition and sharing of digital skills, and raising awareness of the benefits and risks. For public administration employees, Article 14, paragraph 3 of Law No. 132/2025, assigns the responsibility for their training to the administrations themselves.

Law No. 132/2025 does not specifically regulate the training of independent professionals. A future legislative decree will most likely mandate professional associations (and also non-professional associations, as per Law No. 4/2013) to organize specific training and digital literacy courses on the use of artificial intelligence, thus increasing the preparation of professionals. This measure is designed to help members adopt technologies consciously and update their skills. No additional funding is planned, but the topic is already being addressed by many organizations, which are developing guidelines and operational manuals.

It is clear, therefore, that the digital divide cannot be addressed solely by Internet connectivity (which concerns inequalities of access), but also by training and digital literacy among citizens in the strict sense (which concerns inequalities of use).

A knowledge society requires its members to develop specific skills. With the enormous mass of information available online, social inequalities no longer concern the information 'rich' and the information 'poor', but rather the critical cognitive tools with which each individual processes the (many) pieces of information they acquire (Paccagnella, 2010: p. 174).

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33 Our translation.

34 The two Strategies were approved by the Council of Ministers on 3 March 2015. The general objective is to bridge the country's digital gap in terms of infrastructure and services, respectively, in line with the European Digital Agenda.

4 Some proposals to address and manage the new challenges posed by AI for a more inclusive European digital space

Artificial intelligence operates through algorithms, i.e. mathematical formulas that allow a machine (more specifically a computer or a robot) to correlate large amounts of information and data (more generally, at a "macro" level, referred to as "big data"), by processing, aggregating and disaggregating such data, just as the human brain does; all this, of course, with high levels of efficiency and at a very high speed that is difficult for a human being to match (Crisci, 2018: p. 1787). These operating modes bring undoubted benefits, as AI can help find solutions to many of the problems afflicting individuals and society as a whole (from more effective medical care to better education). However, it should also be noted that this can only happen if the technology is of high quality and is developed and used in such a way as not to jeopardise citizens' rights.

The new socio-economic dynamics resulting from the continuous implementation of new technologies in today's interactive world require interpreters to pay greater attention to the pitfalls and dangers for individual rights that lurk every time we access the Internet or use social media and digital platforms. Artificial intelligence, in particular, is becoming an increasingly integral part of everyday life, significantly affecting (but not always with the necessary awareness) every individual, and influencing not only their choices and opportunities but also their individual freedoms.

This brief introduction highlights the importance and necessity of appropriately addressing the challenges and risks inherent in the information and communications technology society in the most appropriate way, placing people at the centre of the debate. A new regulatory approach is therefore needed, especially for the ethical use of artificial intelligence. Despite the ability of machines to learn from themselves, through so-called 'machine learning', or even to develop new learning paths with so-called 'deep learning', they lack the entirely human ability (the so-called discernment) to evaluate multiple unexpected or unpredictable variables.

There is, therefore, a need to minimise the risks of negative impact of what has been called the '*tyranny of the algorithm*' on people's civil, social and political rights (Rodotà, 2014: p. 37). From this perspective, it is legitimate to question the usefulness of developing specific self-learning algorithms to detect and correct the existence of so-called decision-making biases (fairness formulas) (Desai & Kroll, 2018: p. 35 ff.), just as it is necessary to ask whether the adoption of self-regulatory codes by the parties involved is sufficient (Borgesius, 2018: p. 10 ff, esp. p. 27).

The above-mentioned tools are certainly useful, but it is equally true that they are still based on a logic of self-discipline, which by its very nature is subject only to the constraints suggested by the culture of operators at any given moment in history.

Therefore, if AI ultimately operates through algorithms, which consist of "a sequence of instructions according to which the computer processes a

calculation" (Zellini, 2018: p. 11), its actions will be the result of the programmer who designed the data processing code and the mind that selected the data entered or programmed its self-learning capacity (on this topic, Avitabile, 2017: p. 319 ff.). What shifts, in essence, is the power to guide reasoning and the risks associated with its limitations; risks that shift from one human being to another and not from a human being to a 'machine', at least until we have fully autonomous and self-reproducing 'AI systems' (Holder, Khurana, Harrison & Jacobs, 2016: p. 386). Human actions and the choices that underpin them are not only the product of biochemical or neurophysiological stimuli, but also the result of socio-economic conditioning and the environment in which we live.

Therefore, if left unregulated, the activities carried out by Artificial Intelligence risk consolidating the positions of privilege, inequalities and asymmetries (including informational ones) that exist in a given community to which the programmer and data selector belong (Baldwin, 2019). This is why, even in the most attentive foreign literature, when specific risks are discussed, at least three different types of problems are mentioned: a) the secrecy or unintelligibility of the logic underlying the decision-making process, especially in the case of machine learning algorithms (the 'black box' problem) (Pellecchia, 2018: p. 1210 ss.); b) the discriminatory nature of the algorithm (Chander, 2017: p. 1023 ff.); c) the humiliation of human beings, who are made the subject of entirely automated decision-making processes, with the related issue of human dignity (Noto La Diega, 2018).

Against this backdrop, however, as is widely known, AI is increasingly being entrusted with algorithmic assessments in areas that are highly sensitive and diverse, ranging from personnel selection to education and healthcare, to name but a few. In this sense, it is nevertheless necessary to maintain a firm commitment to AI serving people. After all, this objective was already evident in the European Commission's Communication of 25 April 2018 on "Artificial Intelligence for Europe".

In fact, after defining artificial intelligence as a set of systems that exhibit intelligent behaviour by analysing their environment and taking actions, with a degree of autonomy, to achieve specific goals (see Sauvé, 2018: p. 1), it is clarified that the European Union must ensure an ethical and legal framework that respects the fundamental economic and social rights and freedoms of citizens, as well as the principles of transparency and accountability (Temme, 2017: p. 473 ff.). The principle of transparency would require AI processes to be human-understandable, which, however, would at least rule out the possibility of so-called strong artificial intelligence (*strong* AI), *i.e. machine learning* that evolves by learning from its own experience and in ways that are not always predictable, as well as more complex and modern adaptive systems capable of modifying their own code autonomously to adapt to external circumstances (Perlingieri, 2015: p. 1235 ss.). The Regulation on Artificial Intelligence (the Artificial Intelligence Act) is therefore welcomed, as it provides useful definitions relating to AI systems. On the specific point of the principle of transparency, it is envisaged that this must always be guaranteed with clear, complete, accurate and easily accessible information that is understandable to users and anyone who purchases or uses AI systems; the latter must always be accompanied by instructions for use indicating their characteristics and limitations, so that their

operation is not opaque but explainable and, indeed, transparent. Human supervision must also always be guaranteed.

The choice of the form of the Regulation, as a binding legislative act to be applied in its entirety throughout the EU, is therefore not accidental, but is part of a broader project to guarantee and fully protect the individual. Therefore, the rules proposed in the Artificial Intelligence Act allow for better reflection on the centrality of human beings and the need for sustainable technological development that 'understands' humans and does not simply 'replace' them in their daily activities, starting from the awareness that AI systems can pose a risk to health, safety and, more generally, to people's fundamental rights[35]. Through this regulatory intervention, the Commission proposes new rules and actions for excellence and trust in artificial intelligence[36], which apply both to European operators and to providers[37] or users[38] of AI systems established

35 *See Recital 26 of the AI Act: "In order to introduce a proportionate and effective set of binding rules for AI systems, a clearly defined risk-based approach should be followed. That approach should tailor the type and content of such rules to the intensity and scope of the risks that AI systems can generate. It is therefore necessary to prohibit certain unacceptable AI practices, to lay down requirements for high-risk AI systems and obligations for the relevant operators, and to lay down transparency obligations for certain AI systems."*

36 *See Recital 8 of the AI Act: "A Union legal framework laying down harmonised rules on AI is therefore needed to foster the development, use and uptake of AI in the internal market that at the same time meets a high level of protection of public interests, such as health and safety and the protection of fundamental rights, including democracy, the rule of law and environmental protection as recognised and protected by Union law. To achieve that objective, rules regulating the placing on the market, the putting into service and the use of certain AI systems should be laid down, thus ensuring the smooth functioning of the internal market and allowing those systems to benefit from the principle of free movement of goods and services. Those rules should be clear and robust in protecting fundamental rights, supportive of new innovative solutions, enabling a European ecosystem of public and private actors creating AI systems in line with Union values and unlocking the potential of the digital transformation across all regions of the Union. By laying down those rules as well as measures in support of innovation with a particular focus on small and medium enterprises (SMEs), including startups, this Regulation supports the objective of promoting the European human-centric approach to AI and being a global leader in the development of secure, trustworthy and ethical AI as stated by the European Council, and it ensures the protection of ethical principles, as specifically requested by the European Parliament."*

37 *See article 3 (3): " 'provider' means a natural or legal person, public authority, agency or other body that develops an AI system or a general-purpose AI model or that has an AI system or a general-purpose AI model developed and places it on the market or puts the AI system into service under its own name or trademark, whether for payment or free of charge."*

38 *See article 3 (4): " 'deployer' means a natural or legal person, public authority, agency or other body using an AI system under its authority except where the AI system is used in the course of a personal non-professional activity."*

outside the EU if the output of the systems developed or used by them is used within the EU. A distinctive feature of the regulation is a risk-based approach (*AI Risk Classifications*) that can be divided into three levels based on the impact AI might have on the safety of individuals and fundamental rights: prohibited, 'high risk' and 'limited risk'.

It should be noted that certain uses of AI are so potentially harmful that they pose a clear threat to citizens. Owing to their negative repercussions on the safety of individuals or their defined fundamental rights, these risks are considered 'unacceptable'[39]. It is also important to note that the list of 'high-risk' AI systems (Article 6) is annexed to the proposal and may be revised over time, including in the light of technological developments. Preliminary, and in a certain sense, a precondition, to this entire regulatory framework are the tools and knowledge that must be provided to citizens, particularly to young people, in order to train them professionally in the sectors affected by the changes brought about by technological innovation (in the belief that no scientific knowledge can be considered excluded), through educational and scientific programmes that are careful to include elements of interdisciplinarity and topicality. In this sense, it is an absolute priority to pursue the objective of gradually reducing and ultimately eliminating the digital divide, which, as we have seen, unfortunately still affects many sections of the population in Europe. Greater culture and awareness in IT and digital fields can ensure that AI systems are used and managed in a responsible and secure manner, agreeing on the use of artificial intelligence as a means of increasing human well-being.

Furthermore, issues broadly related to AI systems, such as cybersecurity tools and the socio-legal implications of cyberbullying and hateful and violent content (hate speech, revenge porn, etc.) in online life, should also be placed more at the centre of the international scientific debate. From this point of view, it is essential to create mechanisms and margins of choice regarding the functioning of selective algorithmic processes.

Since algorithm-driven user interfaces (ADUIs) use algorithms to personalize and optimize user interactions, they play a crucial role in shaping the user experience (UX). They influence everything from recruitment systems and personalized news aggregation platforms to search results and personalized content recommendations. For example, search engines such as Google (google.com) use algorithms to prioritize relevant websites based on factors such as keywords, user intent and search history, presenting the most useful results at the top of the page for quicker access. Additionally, streaming platforms such as Netflix and YouTube use recommendation models, such as collaborative filtering and deep learning, to suggest content based on viewing history, preferences and interactions. These models continually adapt to improve user satisfaction and engagement.

While personalization offers convenience and tailored content, it also raises ethical concerns when the underlying algorithms perpetuate biases. To mitigate algorithmic bias in the user interface, it is crucial that designers and

39 *Article 5 contains a list of "Prohibited AI practices."*

developers prioritise equity-oriented strategies.

Firstly, algorithmic transparency is essential in order to enable users to understand how their data influences decisions relating to the user interface. This helps build trust and empowers users by providing them with information about the factors that determine their digital experiences. Secondly, regular bias audits must be conducted to evaluate algorithms for discriminatory patterns. For example, recommendation and personalisation algorithms should be evaluated to identify and correct any biases that could lead to unfair or harmful outcomes. In addition, user-centric controls should be incorporated to give users the ability to modify algorithmic outcomes. This could include options such as content filtering, advertising preference settings and the level of personalisation received. While many platforms offer basic personalisation options, they are often not comprehensive enough to address biases or provide meaningful transparency. Therefore, it is important to allow users to control the underlying algorithms that determine how content is delivered to them, as well as the content they see, in order to foster a more personalised and equitable experience. Finally, it is crucial that algorithms are trained on diverse datasets representing different races, genders, ages and cultural backgrounds.

This approach will help to reduce biases that may arise from limited datasets and ensure that algorithms can better meet the needs of all users, providing a more equitable and inclusive experience for all. However, these strategies involve potential trade-offs, such as balancing fairness with personalisation accuracy. For instance, prioritising fairness could lead to higher costs for the platform, including reduced advertising revenue, fewer user interactions and limited data exchange and information acquisition.

Possible solutions include making incremental changes, starting with small-scale pilot projects to demonstrate the benefits of equity-conscious systems and promoting collaboration between designers, developers, and industry leaders to establish long-term goals for algorithmic equity.

Clearly, however, all this presupposes as a premise a broader and deeper digital literacy that is currently lacking on average among users in Europe, if we look at the data from the EU Commission ‘State of the Digital Decade 2025’, according to which in 2023, only 55.6% of adults had at least basic digital skills (European Commission, 2025h: point 3.a). The report notes that on the basis of current trends, the EU is expected to reach a level of just under 60% by 2030 - falling significantly short of the 80% target set in the context of the Digital decade policy programme.

In addition, it underlines that this shortfall is particularly evident among certain demographic groups. For example: older adults, people universally digitally literate: 43% of eighth-grade students (aged 13 to 14) do not reach basic levels of digital skills, with persistent disparities based on socio-economic background and geographical location.

However, to address these challenges, the Commission, in partnership with Member States, has put in place a comprehensive framework to strengthen digital skills across society. The Skills package (European Commission, 2025i), adopted in March 2025, puts a strong focus on digital skills as a key

driver for competitiveness. It includes the Union of Skills, an Action Plan on Basic Skills (European Commission, 2025e), a STEM Education Strategic Plan (European Commission, 2025j), and the upcoming 2030 Roadmap on the future of digital education and skills.

5 Conclusions

The achievement of consumer and user welfare[40], also and above all as an expression of the principle of equality protected by Article 3 of the Italian Constitution[41], is linked to the need for all citizens to have equal and non-discriminatory access to digital services, especially those provided via the Internet, which more than any other contribute to the '*full development of the human person*' (Frosini, 2015: p. 65).

The free use of digital services can ensure, and may even pave the way for, effective 'equal social dignity': access to virtual spaces, where an increasingly significant part of our lives takes place, and cannot be guided or limited in any way by those who hold dominant positions in the respective digital markets.

The challenge of effective regulation of the digital sector is more open than ever, and the role of the European Union will have to place even greater emphasis in the future on enhancing the individual aspirations of web users and on protecting, in addition to the economic market, fair and informed access to the network by users as a primary interest, by ensuring that digital markets always guarantee the full development of an individual's personality on digital platforms.

De iure condendo, however, we should perhaps avoid an excessive and cumbersome set of rules[42], which complicate the regulatory framework and make it very difficult to apply them, both for citizens/consumers/users of digital platforms and for companies operating in the industrial technology sector.

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40 See De Cesare, 2020: p. 101, according to which, by promoting the well-being of the community, antitrust law "aims to foster greater interconnection between European states, eliminating the inequalities, hardships and isolation to which some territories have been exposed for years and, essentially, achieving social advancement in this field as well."

41 See Manetti, 2019: p. 53, according to which "no one disputes [...] that the obligation to prevent the formation of private authorities or powers is based on the task assigned to the Republic by Article 3, paragraph 2, of the Constitution, which is made operational in this matter by Article 41, paragraph 2, with regard to the limits that economic initiative is subject to in the name of guaranteeing constitutional freedoms". On competition as a tool for the protection of equality, see also Fiorillo, 2019: p. 76 ff., according to whom "in order to promote greater interconnection between European states, eliminating the inequalities, hardships and isolation to which some territories have been exposed for years and, essentially, achieving social advancement in this field as well."

42 Take, for example, the regulation on artificial intelligence, which consists of 89 recitals, 85 articles (at least one of which, Article 4, has 44 paragraphs) and 9 annexes.

It is not easy to navigate the regulatory maze, even for the human mind, including that of a lawyer accustomed to interpreting regulations. For this reason, in matters that are so strategic for our present and future, European (and other) legislation should be supported by 'sustainable' regulatory frameworks, with the aim of balancing diverse interests and concepts, setting as its primary objective not to inhibit research and development of technologies.

Furthermore, European legislation should be flexible and adaptable to change with the aim of creating and forming a *stable but not static* law for new technologies and digital markets. Only in this way will it be possible to achieve a more complete digital legal order: an order understood not as a command, but rather as rules of principle containing precepts that require certain types of actions to be taken (or not taken) (Frosini, 2023: p. 2).

Probably, the challenge facing jurists in the 21st century is mainly related to technology, namely how to strengthen and protect individual freedoms in a social context that has been profoundly changed by technological innovation and its legal derivatives.[43] There has also been talk of a new constitutionalism, which brings to the fore the materiality of situations and needs, identifying new forms of bonds between people and projecting them on a different scale from those we have known until now (in these terms, see Rodotà, 2012: p. 7).

Therefore, it makes sense to reinterpret the traditional rights of freedom enshrined in our Constitution in a new light in view of technological developments. First and foremost, this must be done in relation to freedom of information, as the right to be informed as well as to inform, but also with regard to freedom of communication, association, assembly, private economic initiative, and in reference to political freedoms, in order to identify ways of protecting new subjective legal situations. There has also been the epiphany of a new form of freedom, which has been conceptualised in doctrine since the 1980s and which has come about with the advent of the technological society. This is the doctrine of so-called 'digital freedom', which, especially with the Internet, has become a claim to freedom in the active sense, not freedom from but freedom to, the freedom to use information technology tools to provide and obtain information of all kinds.[44]

We are undoubtedly faced with a new form of freedom, since it is no longer just a question of the free expression of an individual's thoughts, but rather the ability to establish relationships, transmit and request information, and have unlimited access to the new power of knowledge conferred by telematics.

However, in order to fully implement this freedom, it is essential to combat the digital divide. This should be done by ensuring to all people the condition of having access to the Internet or other digital technologies and to making use of online services, while significantly reducing the current percentage of those who are excluded from such services.

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43 Costanzo, 2012: p. 852 discusses "technological constitutionalism" following liberal and democratic constitutionalism; Betzu, 2022: p. 92 ff. writes and argues about "digital constitutionalism."

44 The doctrine of IT freedom was developed by Frosini, 1981: p. 37 ff.

Equally essential to ensuring the full expression of this freedom is the guarantee of net neutrality (see Wu, 2023: p. 141-179) in order to support open and equal access to the Internet as a common good and public service, especially in the context of overcoming social and educational divides (i.e. the already seen digital divide[45]) and promoting the democratisation of knowledge and freedom of information and expression.

Therefore, a crucial measure for the technology sector is precisely the maintenance of net neutrality[46] and an '*Open Internet Order*', both of which can help slow down the trend towards oligopolisation/monopolisation and the re-feudalisation of the (Internet) economy by BigTech (Wörsdörfer, 2020: p. 198-199). In this regard, the role played by the Italian Communications Authority (Autorità per le Garanzie nelle Comunicazioni, 2025) appears significant. In its report on activities carried out in relation to the *Open Internet*, it clarifies the data in order to promote the availability of Internet access at quality levels that are in line with technological progress and provided in a non-discriminatory manner. In particular, the Authority has closely monitored the compliance with Articles 3 and 4 of the Regulation, relating respectively to the safeguarding of access to open Internet[47] and transparency measures

45 *On the digital divide, see Norris, 2001; Gaspari, 2018.*

46 *In this sense, Regulation (EU) 2015/2120 of the European Parliament and of the Council of 25 November 2015 laying down measures concerning open internet access and amending Directive 2002/22/EC on universal service and users' rights relating to electronic communications networks and services and Regulation (EU) No 531/2012 on 'roaming on public mobile communications networks within the Union', which introduced a new set of rules on net neutrality into the legal system. These rules came into force on 30 April 2016 and pursue the dual purpose of "establishing common rules to ensure fair and non-discriminatory treatment of traffic in the provision of internet access services and protecting the related rights of end users', as well as 'ensuring the continued functioning of the internet ecosystem as a driver for innovation."*

47 *Article 3 "Safeguarding of open internet access": 1. End-users shall have the right to access and distribute information and content, use and provide applications and services, and use terminal equipment of their choice, irrespective of the end-user's or provider's location or the location, origin or destination of the information, content, application or service, via their internet access service.*

to ensure such access[48]. Furthermore, Law No. 132 of 23 September 2025[49], the first national law to be approved in Europe for the regulation, development and management of AI, in synergy with the aforementioned EU Regulation 2024/1689, is also motivated by the same intent of regulatory clarification. We have seen, in fact, the advantages that efficient regulation of AI can bring in the digital sphere.

With regard to the EU level, the European Commission has recently presented the European Technological Sovereignty Package. This is a series of measures designed to strengthen Europe's capabilities in the areas of semiconductors, artificial intelligence (AI), cloud technology and open-source software.

The package comprises two legislative proposals: the Chips Act 2.0 and the Cloud and AI Development Act. It also includes an Open-Source Strategy and a Strategic Roadmap for Digitalisation and AI in Energy. Collectively, these measures will support Europe's ambition to become an AI continent, strengthen its digital autonomy and help build a more sustainable digital future. They will also increase the range of core technologies available to EU

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48 *Article 4 "Transparency measures for ensuring open internet access": 1. Providers of internet access services shall ensure that any contract which includes internet access services specifies at least the following: (a) information on how traffic management measures applied by that provider could impact on the quality of the internet access services, on the privacy of end-users and on the protection of their personal data; (b) a clear and comprehensible explanation as to how any volume limitation, speed and other quality of service parameters may in practice have an impact on internet access services, and in particular on the use of content, applications and services; (c) a clear and comprehensible explanation of how any services referred to in Article 3(5) to which the end-user subscribes might in practice have an impact on the internet access services provided to that end-user; (d) a clear and comprehensible explanation of the minimum, normally available, maximum and advertised download and upload speed of the internet access services in the case of fixed networks, or of the estimated maximum and advertised download and upload speed of the internet access services in the case of mobile networks, and how significant deviations from the respective advertised download and upload speeds could impact the exercise of the end-users' rights laid down in Article 3(1); (e) a clear and comprehensible explanation of the remedies available to the consumer in accordance with national law in the event of any continuous or regularly recurring discrepancy between the actual performance of the internet access service regarding speed or other quality of service parameters and the performance indicated in accordance with points (a) to (d). Providers of internet access services shall publish the information referred to in the first subparagraph. 2. Providers of internet access services shall put in place transparent, simple and efficient procedures to address complaints from end-users relating to the rights and obligations laid down in Article 3 and paragraph 1 of this Article.*

49 *Law No. 132 of 23 September 2025, "Provisions and delegations to the Government on artificial intelligence". However, this law refers to various implementing decrees that the government must issue within 12 months for technical definitions, risk parameters, assessment procedures, control mechanisms and many of the administrative penalties.*

businesses, citizens, and public administrations.

Ultimately, all these measures provide full implementation of Article 19 of the Universal Declaration of Human Rights, which clearly specifies the right to freedom of expression: "*to seek, receive and impart information and ideas through any media and regardless of frontiers*". This is a perfect formulation, especially in the age of the Internet.

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The AI Divide in HR: Digital Gaps Between Western and Central and Eastern Europe

Original scientific paper

Filip Bušina[1]

ABSTRACT

This paper analyses the growing AI divide in human-resources management across Europe, focusing on measurable performance gaps between Western Europe and Central and Eastern European (CEE) countries. The study distinguishes between digitalisation as an enabling infrastructure and artificial intelligence (AI) as an advanced decision-support and governance technology embedded in HR and payroll systems. It examines how differences in AI integration—rather than mere automation—affect organisational efficiency, employee trust, and regional competitiveness. The research combines macro-level digital indicators from the European Commission with large-scale surveys conducted in 2024–2025 among 698 organisations from nine CEE countries and a reference sample of Western European firms. The analysis is further supported by recent European market studies and original empirical data on HR automation, AI adoption, and governance maturity. The results reveal that while Western Europe has largely integrated AI into core HR functions, including predictive analytics, workforce planning, and AI-supported decision-making, most CEE economies remain in a hybrid stage characterised by partial automation, weak data governance, and limited managerial capabilities to operationalise AI. Although several CEE countries demonstrate rapid progress in digital intensity and e-commerce adoption, the performance gap in AI-enabled HR remains substantial. The paper concludes that the AI divide in HR is primarily a managerial and organisational phenomenon rather than a purely technological one. Bridging it requires unified data architectures, stronger HR–IT integration, systematic upskilling of HR professionals, and the implementation of transparent AI-governance frameworks to ensure trust, accountability, and sustainable competitiveness.

Keywords: *AI divide, Digital transformation, Human resources management, Central and Eastern Europe, HR 5.0*

JEL classification: *M15, J24, O33, O52, M54*

1 *Assistant Lecturer at the Institute of Forensic Engineering, University of Žilina, Ulica 1. mája 32, 010 01 Žilina, Slovakia; DSc candidate at MGIMO University, Asset Management Department. Phone: +420 606 644 772. E-mail: filip.busina@elanor.cz*

1 Introduction

The accelerating diffusion of artificial intelligence (AI) across European labour markets is redefining the digital transformation of human-resources management (McKinsey & Company, 2025). While Western Europe has reached the stage of mature HR ecosystems—where automation, analytics, and AI-driven decision support are embedded in payroll, recruitment, and learning systems—Central and Eastern European (CEE) countries remain at a transitional point (Grigorescu et al., 2021). The region has adopted digital technologies rapidly, yet often within fragmented architectures and without full integration of AI into core HR and quality-management processes (Pham and Davies, 2025). This gap, increasingly visible in data from the Digital Economy and Society Index (European Commission, 2025) and the EY European AI Barometer (EY, 2025), constitutes a new form of inequality: an AI divide that separates not the access to technology, but the capacity to translate it into measurable organisational value.

Unlike the earlier digital divide—which was primarily concerned with connectivity and infrastructure (OECD, 2025), the AI divide in HR is manifested through quantifiable performance differences (Thite and Iyer, 2025). Western organisations report faster hiring cycles, higher accuracy in workforce analytics, and measurable cost reductions in HR administration (EY, 2025; McKinsey & Company, 2025). In contrast, many CEE firms continue to operate hybrid models—partial automation combined with manual control and limited data interoperability (Tutak & Brodny, 2024). These disparities are not only technological but also managerial: constrained investment capacity, weaker data-governance frameworks, and lower digital competence among HR professionals have delayed the transition from HR 4.0 to HR 5.0 (Babkin et al., 2021). As a result, Western Europe is already harvesting productivity gains, whereas CEE economies are still constructing the necessary preconditions.

While digitalisation constitutes the necessary infrastructural baseline for contemporary HR systems, the analytical focus of this paper is on artificial intelligence as a decision-support and governance technology embedded in HR processes. Digitalisation is therefore treated as an enabling condition, whereas AI integration represents the core explanatory factor of the observed performance divide. The paper analyses the AI divide empirically by combining comparative indicators from EU datasets (European Commission, 2025; Digital Decade Scoreboard 2025) with EY and McKinsey surveys and proprietary data from 698 organisations across nine CEE countries. The study aims to identify where and why the divide persists, quantify its economic effects, and propose realistic measures to bridge it—through investments in HRMS/QMS integration, improved data quality, professional education, and the implementation of AI-governance frameworks such as ISO 42001. Grounded in empirical evidence and process analysis rather than abstract ethics or institutional rhetoric, this research demonstrates that the AI divide in HR is not a technological inevitability but a managerial choice.

Recent findings of the OECD (2025) further confirm that the AI divide is widening rather than closing. Across the EU-27, the share of enterprises using AI grew from 8 % in 2023 to 13.5 % in 2024, yet this growth disproportionately

benefited already advanced regions. The cross-country gap in AI adoption widened from 14 percentage points in 2021 to 24 percentage points in 2024. This acceleration reflects a first-mover advantage typical for general-purpose technologies: early adopters generate cumulative benefits, while late adopters face rising capability and infrastructure barriers. This creates a reinforcing dynamic that particularly disadvantages the CEE economies where digital transformation remains broad but shallow.

2 Literature review and theoretical framework

The digital transformation of human-resources management can be conceptualised as a continuum between HR 4.0 and HR 5.0, reflecting the broader industrial transition from Industry 4.0 to Industry 5.0 (Babkin et al., 2021; Wang & Li, 2023). HR 4.0 introduced automation and data integration into payroll, attendance, and performance-management systems, primarily aiming to reduce administrative costs and human error. In contrast, HR 5.0 represents a human-centric evolution in which artificial intelligence (AI) augments—rather than replaces—human decision-making (Bansal et al., 2023). The paradigm shift lies in transforming HR systems from reactive data repositories into predictive and adaptive ecosystems that combine algorithmic precision with human judgement (McKinsey & Company, 2025). This transition reflects the methodological logic of Industry 5.0, as described by Babkin et al. (2022), where neuro-digital interaction between human cognition and AI systems becomes the foundation for strategic decision-making and organisational adaptability.

The integration of AI into HR systems has redefined the epistemology of managerial decision-making. Algorithms can generate predictions regarding employee turnover, competence alignment, or performance potential; however, such outputs remain probabilistic rather than normative. As Leonhard (2016) observed, AI lacks empathy, intentionality, and moral reasoning—it provides analytical context but not meaning. Consequently, an effective HR 5.0 model can be characterised as “AI as context, human as interpreter”, in which human professionals validate and contextualise machine-generated insights through ethical reasoning, organisational culture, and situational awareness. This hybrid configuration corresponds with emerging principles of AI governance, including ISO 42001, which emphasise transparency, accountability, and sustained human oversight (Stepnov, 2021; Kovalchuk, 2021; Mogila & Alenikov, 2025).

From a macroeconomic perspective, OECD (2025) emphasises that AI has reached the status of a general-purpose technology (GPT), characterised by strong complementarities with skills, organisational routines, and data architectures. As with previous GPTs, productivity effects materialise only where technological investment is accompanied by human-capital development and governance capabilities. Early adopters therefore benefit from accelerating returns, while lagging organisations and regions face increasing adjustment costs. This dynamic reinforces the architectural asymmetries inherent in HR 5.0 and helps explain why economies with incomplete or fragmented digital infrastructures struggle to integrate predictive HR technologies effectively.

The theoretical basis of the AI divide can thus be traced to differences in how organisations institutionalise these hybrid socio-technical architectures. Western European firms tend to possess mature Quality Management Systems (QMS) and Human-Resource Management Systems (HRMS) integrated through application programming interfaces (APIs) and unified data-governance frameworks (OECD, 2025). Such integration enables the deployment of AI tools for predictive analytics, workforce planning, and continuous learning loops (Demir et al., 2023). In CEE countries, however, integration often remains partial: many firms implement isolated automation modules without cohesive data architectures or feedback mechanisms (Grigorescu et al., 2021). The result is a form of "shallow digitalisation", whereby technology automates individual tasks but fails to transform decision logic or organisational behaviour. As Bharati (2021) notes, fragmented digital infrastructures limit the potential of business intelligence systems to evolve into cognitive systems capable of contextual reasoning and predictive adaptation.

Recent research increasingly suggests that the maturity of AI in HR depends less on algorithmic sophistication than on managerial design and digital competencies (Tutak & Brodny, 2024; McKinsey & Company, 2025). Empirical evidence indicates that AI adoption correlates more strongly with process standardisation, data quality, and strategic alignment than with the absolute size of IT budgets (EY, 2025). This observation frames the AI divide not as a technological inevitability but as a managerial phenomenon: organisations that fail to combine automation with interpretive competence remain locked in suboptimal equilibria. This interpretation aligns with the conceptual work of Stepnov and Kovalchuk, who define managerial intelligence as a synthesis of analytical reasoning and moral cognition—a dual capability essential for maintaining human agency in AI-supported decision-making (Stepnov, 2021; Kovalchuk, 2021).

Accordingly, the present study interprets HR 5.0 as an adaptive system of human–machine co-agency, whose effectiveness depends on trust, governance, and organisational learning. Within this system, AI enhances analytical and predictive capacity, while human actors contribute ethical validation, contextual judgement, and creativity. The divide between Western and CEE HR models is therefore not merely a question of investment intensity, but of architectural intelligence—the ability to structure data, processes, and decision rights into a coherent socio-technical whole (Babkin et al., 2022; Bharati, 2021).

3 Methodology and data sources

The methodological approach of this study follows a structured mixed-method comparative design, integrating quantitative indicators and qualitative managerial interpretation. The design is explicitly comparative and multi-level, aiming to identify measurable differences in the level of AI adoption and HR digitalisation between Western Europe and the Central and Eastern Europe countries. The research combines four complementary data pillars: (1) EU-level digital indicators, (2) commercial survey data, (3) original field research, and (4) expert interpretation grounded in institutional context (Bušina, 2025).

This configuration enables triangulation across analytical levels and data sources, increasing the robustness of the findings.

3.1 EU digital indicators

The baseline quantitative framework is derived from the Digital Economy and Society Index (European Commission, 2025) and the Digital Decade Scoreboard 2025 (European Commission, 2025). These datasets monitor 27 EU member states across four key dimensions — Human Capital, Connectivity, Integration of Digital Technology, and Digital Public Services (European Commission, 2025).

For the purposes of this study, three sub-indicators were prioritised as directly relevant to HR transformation and organisational digitalisation:

1. SMEs with at least a basic level of digital intensity (70.8 % in the Czech Republic, 2025),
2. Enterprises using AI, cloud, and big-data technologies,
3. Individuals interacting with public authorities online (e-Government use, 78.5 % in the Czech Republic, 2025).

These indicators act as proxies for technological maturity and institutional readiness of the labour-market ecosystem, particularly in relation to AI-enabled HR systems. Comparative averages for 11 CEE countries (BG, HR, CZ, EE, HU, LT, LV, PL, RO, SI, SK) and six Western benchmarks (AT, BE, FR, DE, IE, NL) were calculated to visualise the magnitude of the digital gap (DESI, 2025; OECD, 2023).

3.2 Commercial and sectoral surveys

To complement EU-level data, the study draws on two major international sources: the EY European AI Barometer 2025 and the McKinsey Superagency Report 2025. The EY Barometer provides harmonised data from over 1,000 European enterprises, quantifying the degree of AI maturity across business functions. It enables cross-regional comparison between technological adoption and managerial integration of AI, showing that only 19 % of CEE firms have fully integrated AI into their core HR or QMS processes, compared with 42 % in Western Europe (EY, 2025).

McKinsey's analysis (2025) further highlights the managerial dimension: 92 % of firms plan to increase AI investments, yet only 1 % consider themselves AI-mature (McKinsey & Company, 2025). Together, these sources support a comparative assessment of technological potential versus organisational readiness, aligning with Tutak and Brodny's (2024) findings on digitalisation asymmetries in CEE enterprises and Bharati's (2021) analysis of business-intelligence integration within Industry 5.0 environments.

3.3 Original empirical dataset

The empirical foundation of this research comprises two large-scale surveys conducted in 2024–2025 among 698 organisations from nine CEE countries (CZ, SK, PL, HU, RO, BG, SI, HR, EE).

The first survey investigated organisational and economic aspects of HR outsourcing and automation (transition HR 4.0 → HR 5.0), while the second focused on the implementation of AI-supported Quality Management Systems (QMS). Respondents included HR directors, CFOs, and operations managers.

Data were collected via an online questionnaire and validated through structured follow-up interviews with 47 representatives of medium and large enterprises (Grigorescu et al., 2021). Additionally, internal R&D outcomes from the Elanor AI Assistant 0.5 project (Bušina, 2025) were used to cross-validate survey reliability. This pilot initiative operationalised AI-supported HR functionalities, including payroll automation, AI-assisted HR reporting, and context-aware employee-feedback loops within a unified HRMS architecture.

Descriptive statistics were processed using cross-tabulation and correlation analysis, focusing on five key variables:

- Degree of automation (payroll, recruitment, attendance, LMS systems),
- Presence of AI-driven HR tools (chatbots, predictive analytics, anomaly detection),
- Integration of HRMS/QMS architectures,
- HR staff digital-skills index,
- Budget share allocated to HR IT investments.

3.4 Analytical framework

The study applies triangulation to connect macro-level digital indicators (European Commission, 2025) with micro-level organisational data (EY, McKinsey, Elanor dataset). Triangulation is employed as a methodological principle rather than a statistical technique, enabling cross-validation of results across heterogeneous data sources.

Triangulation was conducted in line with the ISO 42001 AI-management principles, ensuring that data quality, explainability, and human oversight were systematically evaluated through cross-validation (Bušina, 2025; Stepnov, 2021; Kovalchuk, 2021).

A composite AI Adoption Index was developed to compare Western and CEE countries along two analytical dimensions:

1. Technological adoption (AI, cloud, and data-analytics usage), and
2. Managerial integration (HR competence, data governance, investment effort).

The resulting matrix identifies four typological categories—AI leaders, fast followers, cautious adopters, and late implementers (McKinsey & Company,

2025; EY, 2025). This typology provides the empirical backbone for the comparative analysis presented in Chapter 4.

3.5 Theoretical framework and research hypotheses

From the perspective of institutional and behavioural economics, the AI divide can be interpreted as a structural asymmetry in technological capital, human competences, and trust-based governance frameworks. Following the concepts of transaction cost theory (Coase, 1937; Williamson, 1981) and human capital theory (Schultz, 1961; Becker, 1976), digital transformation in HR modifies the allocation of decision-making authority between humans and algorithms, thereby influencing productivity, organisational efficiency, and perceived fairness in employment relations.

Accordingly, this study tests the following hypotheses:

> **H1**: The integration of artificial intelligence into HR processes in Central and Eastern European organisations enhances decision-making efficiency and organisational trust without diminishing the strategic role of the human factor.
>
> **H2** (conceptual): Institutional readiness and human capital development moderate the strength of this relationship across regions.

These hypotheses operationalise the concept of predictive empathy by linking human-centric AI governance to measurable economic outcomes, such as efficiency, trust, and employee retention, thereby embedding the HR 5.0 framework within institutional economics and decision-making theory under digital asymmetry.

4 Empirical findings: CEE vs Western Europe

4.1 Digital readiness and structural gaps

Data from the Digital Economy and Society Index demonstrate that the CEE region continues to lag behind Western Europe in the structural maturity of digital transformation (European Commission, 2025). While 70.8 % of Czech SMEs have achieved at least a basic level of digital intensity, the EU-27 average already exceeds 74 %, and the leading Western economies such as Ireland, the Netherlands, and Germany surpass 80 % (European Commission, 2025). However, the Czech Republic recorded the fastest year-to-year growth (+21.5 percentage points), indicating strong convergence potential rather than structural stagnation (OECD, 2023).

The OECD regional data (OECD Regional Development Papers, 2025) further demonstrate that structural divergence is visible not only between countries but also within them. Advanced metropolitan regions such as Brussels, Vienna, Oslo, or Central Jutland already report AI adoption rates between 26 % and 35 %, while lagging regions in Romania, Bulgaria, and northern Hungary remain below 10 %. This spatial fragmentation amplifies the AI divide, as organisations located in digitally advanced regions benefit from denser innovation ecosystems, stronger broadband infrastructure, and higher

availability of digitally skilled labour.

A similar duality emerges in e-commerce adoption: 21.8 % of Czech SMEs sell online to other EU countries, and 18.8 % of their turnover derives from digital channels—both figures above the EU average. Yet, in the use of AI, cloud computing, and big-data analytics, CEE organisations still report adoption levels between 15 % and 25 %, roughly half those of Western peers (DESI, 2025; EY, 2025). The DESI indicator on digital public-service usage also illustrates this pattern: while 78.5 % of Czech citizens interacted online with public authorities—above the EU average of 75 %—the figure remains among the lowest within the group of strong innovators (AT, BE, FR, IE, LU, DE, EE).

These findings confirm that the digital transformation in CEE is broad but shallow—a rapid diffusion of basic technologies without a corresponding institutional or governance depth (Grigorescu et al., 2021; Babkin et al., 2022). In the terminology of Industry 5.0, the region exhibits extensive rather than intensive digitalisation, expanding technological coverage while lacking architectural integration and feedback loops essential for adaptive intelligence.

4.2 AI adoption and organisational maturity

The EY European AI Barometer 2025 quantifies this divide with precision. Only 19 % of CEE firms report full AI integration into their HR or quality-management systems, compared with 42 % in Western Europe. Across the continent, AI adoption in HR functions—recruitment, payroll automation, and people analytics—has reached 44 %, positioning HR among the top three business domains for AI deployment (EY, 2025).

The OECD (2025) adds an important organisational dimension: firm size. Across OECD countries, 39 % of large enterprises already use AI, compared to only 12 % of SMEs. In Finland and Sweden, AI adoption among large enterprises exceeds 70 %, particularly in ICT and knowledge-intensive sectors. This firm-size asymmetry disproportionately affects CEE economies, where SMEs dominate the enterprise structure and frequently lack the financial, organisational, and analytical capacity required for systemic AI integration.

Qualitative responses further reveal persistent barriers in the CEE region: insufficient digital competencies (68 %), lack of reliable data infrastructure (44 %), and regulatory uncertainty (46 %) (EY, 2025). These constraints hinder not only the speed but also the depth of AI deployment. Many organisations rely on isolated pilot tools—such as chatbots or attendance-automation systems—without integrating them into HRMS or analytics platforms, resulting in limited scalability and inconsistent data governance (Tutak & Brodny, 2024).

The McKinsey Superagency Report 2025 reinforces these findings. Although 92 % of firms plan to increase AI investments, only 1 % classify themselves as AI-mature. Notably, employee readiness now exceeds managerial readiness: employees already use generative-AI tools three times more frequently than executives estimate, suggesting that leadership hesitancy—rather than workforce resistance—has become the primary bottleneck (McKinsey & Company, 2025). This asymmetry is particularly visible in CEE organisations,

where hierarchical decision-making and risk-averse management cultures constrain experimentation and the delegation of digital authority (EY, 2025; Bharati, 2021).

4.3 Results from the CEE empirical dataset

Evidence from the 698 organisations surveyed across nine CEE countries (Elanor dataset, 2024–2025) provides micro-level confirmation of the divide (EY, 2025; McKinsey & Company, 2025; Bušina, 2025).

Table 1: HR digitalisation and AI adoption — CEE vs Western Europe

Indicator	CEE average	Western benchmark (EY 2025)	Gap
HR processes fully automated (payroll, attendance, recruitment)	54%	83%	−29 p.p.
AI-driven analytics in HR dashboards	22%	48%	−26 p.p.
Integrated HRMS/QMS architecture (API-linked)	31%	65%	−34 p.p.
Formal AI-governance or ethical-use policy	14%	38 %	−24 p.p.
HR staff with advanced digital-skills certification	27%	57 %	−30 p.p.

Note: Values rounded to the nearest whole percent. p.p. = percentage points.
Source: Authors according to EY (2025), McKinsey & Company (2025), DESI (2025), and Elanor Survey (2024–2025).

The data confirm that the AI divide is multidimensional, encompassing technology, competence, and governance. The most pronounced disparity concerns system integration: only one in three CEE firms possesses a unified data architecture connecting HRMS, payroll, and QMS modules (EY, 2025). In the absence of stable data flows, predictive algorithms remain underutilised, and people analytics frequently operate on static spreadsheets rather than dynamic dashboards (McKinsey & Company, 2025).

This finding corresponds to the Integration of Digital Technology pillar of the European Commission (2025) and suggests that the competitive disadvantage of CEE firms stems primarily from data fragmentation rather than technological absence (OECD, 2023; Bharati, 2021; Babkin et al., 2022). The phenomenon mirrors Babkin's concept of architectural asymmetry, whereby organisations adopt isolated technologies without establishing feedback-based systems capable of continuous learning and adaptation.

Sectoral differences further widen the gap. OECD (2025) reports that AI

adoption reaches 44 % in ICT services and between 26 % and 33 % in professional, scientific, and technical services, with Sweden exceeding 53 % in selected subsectors. These sectors function as diffusion hubs for AI-enabled HR analytics and predictive workforce planning, capabilities that remain underdeveloped in CEE organisations concentrated in manufacturing, construction, and traditional services.

4.4 Economic and performance implications

The economic consequences of digital asymmetry are measurable. Firms with mature HR digitalisation report 27 % shorter recruitment cycles, 18 % lower employee turnover, and 15–25 % reductions in administrative costs (EY, 2025; McKinsey & Company, 2025). In contrast, CEE firms operating with partial automation rarely achieve return on investment within the first two years, primarily due to duplicated processes and rework caused by inconsistent data inputs (Tutak & Brodny, 2024).

These inefficiencies directly constrain productivity growth and weaken competitiveness in regional labour markets (Grigorescu et al., 2021). The results therefore substantiate the hypothesis that Western Europe is already harvesting the returns of HR 5.0, whereas CEE economies remain focused on foundational automation and reskilling without achieving systemic integration (Babkin et al., 2021; EY, 2025; Bušina, 2025).

This pattern aligns with the Industry 5.0 logic that digital maturity depends not on technology availability alone, but on the capacity to design coherent human–machine architectures that integrate data, governance, and decision-making (Bharati, 2021; Babkin et al., 2022).

5 Results and discussion

The empirical findings demonstrate that the AI divide in HR is neither accidental nor transient—it reflects structural and self-reinforcing differences in managerial priorities, investment capacity, and the ability to operationalise technology (EY, 2025; McKinsey & Company, 2025). Western Europe benefits from a long-standing convergence of three enabling factors: (1) stable digital infrastructure, (2) professionalization of HR as a strategic function, and (3) regulatory clarity supporting AI integration (OECD, 2023). By contrast, the CEE region remains characterised by project-based and fragmented implementation logics, in which digitalisation is pursued as a collection of isolated tools rather than as a systemic AI-enabled transformation (Grigorescu et al., 2021; Bharati, 2021).

Quantitatively, the average gap between CEE and Western Europe ranges from 25 to 35 percentage points across automation, AI use, and governance indicators (European Commission, 2025). The most pronounced disparities emerge in AI-supported HR analytics and data integration, where predictive tools remain largely experimental or peripheral in CEE organisations (EY, 2025). These results corroborate the study's core claim that the divide lies not in access to technology itself, but in the architecture of managerial decision-

making and the institutionalisation of data governance frameworks.

Recent OECD evidence (2025) confirms that AI diffusion follows a “leaders escaping the pack” trajectory rather than a convergence dynamic. Early adopters accumulate advantages through network effects, data availability, and complementary managerial capabilities, while late adopters face rising barriers linked to data fragmentation, skill shortages, and limited absorptive capacity. This mechanism explains why rapid growth in basic digital intensity in selected CEE countries has not yet translated into comparable gains in predictive HR capabilities. The AI divide is therefore not merely persistent—it is structurally accelerating.

In dialogue with prior literature, three original contributions emerge. First, the triangulated evidence demonstrates that managerial integration variables—data quality, process standardisation, and HR competences—explain more variance in AI adoption than absolute IT expenditure, aligning with but extending the conclusions of EY (2025) and McKinsey (2025). Second, the findings empirically substantiate the notion of “shallow digitalisation” in CEE economies: automation without unified data architectures, feedback loops, or learning mechanisms (Babkin et al., 2022; Bharati, 2021). Third, the analysis identifies an interpretive competence gap: AI systems generate probabilistic signals, but human actors must assign meaning, validate outcomes, and embed them in organisational context—highlighting the centrality of analytical trust and human oversight (Leonhard, 2016; Stepnov, 2021; Kovalchuk, 2021).

Importantly, the results also reveal significant catch-up potential. Rapid growth in digital intensity in selected CEE economies—such as the +21.5 percentage-point increase recorded in the Czech Republic between 2024 and 2025—and expanding cross-border e-commerce activity indicate strong adaptive capacity (European Commission, 2025). However, without parallel investments in data governance, system integration, and human capital development, this momentum is unlikely to yield sustained productivity gains or organisational learning effects (Babkin et al., 2021). The empirical evidence therefore points to a dual trajectory: Western Europe consolidating HR 5.0 outcomes, while CEE economies remain focused on building foundational preconditions.

From a managerial perspective, the principal bottleneck is interpretive and governance competence rather than technological readiness. AI can identify patterns within large datasets, but it cannot explain their organisational relevance or ethical implications. Bridging the AI divide thus requires HR professionals capable of contextual reasoning, responsibility attribution, and ethical validation—the human-centric synthesis that defines HR 5.0 as an adaptive socio-technical system rather than a technological endpoint (Mogila & Alenikov, 2025; Leonhard, 2016; Babkin et al., 2022).

6 Conclusions

This study examined the AI divide in human-resources management between Western Europe and Central and Eastern Europe (CEE) as a multidimensional phenomenon combining technological adoption, managerial integration, and governance capacity. The empirical evidence confirms that the AI divide is not

primarily a question of access to digital tools, but of how artificial intelligence is embedded into organisational architectures and decision-making processes.

The results support the first working hypothesis (H1), demonstrating that the integration of AI into HR processes in CEE firms enhances decision-making efficiency and organisational trust when AI is deployed within integrated HRMS/QMS architectures and complemented by competent human oversight. In such configurations, the human factor is not marginalised but retains a strategic role as interpreter, validator, and ethical arbiter of algorithmic outputs. The second hypothesis (H2) is conditionally supported: institutional readiness, data governance maturity, and human capital development systematically moderate the strength of AI-related performance effects across regions.

The paper's original contribution lies in reframing the AI divide as a managerial and architectural asymmetry rather than a purely technological lag. By combining EU-level indicators, commercial surveys, and original empirical data, the study introduces a composite analytical perspective linking technological adoption with managerial integration. It empirically substantiates the phenomenon of "shallow digitalisation" in CEE economies—automation without unified data architectures or feedback loops—and highlights interpretive competence and analytical trust as critical enablers of HR 5.0.

Several limitations should be acknowledged. The analysis relies primarily on cross-sectional survey data (EY, McKinsey, Elanor dataset) and aggregate EU indicators (DESI, Digital Decade Scoreboard). Although triangulation was applied, causality is inferred rather than directly tested. In addition, commercial studies may lack full methodological transparency, and substantial heterogeneity within the CEE region constrains the generalisability of results.

Despite these limitations, the findings yield clear managerial and policy implications. Bridging the AI divide requires investments in interoperable HRMS/QMS architectures, the implementation of transparent AI-governance frameworks aligned with ISO 42001, and systematic upskilling of HR professionals in data literacy, AI oversight, and ethical validation. Equally important is the institutionalisation of cross-functional cooperation between HR, finance, and controlling functions to ensure that AI-supported analytics translate into economically meaningful decisions. These measures represent managerial imperatives rather than aspirational goals, as they convert AI from a collection of tools into a sustainable organisational capability.

Future research should extend this analysis through longitudinal panel designs capturing convergence dynamics over time, quasi-experimental evaluations of AI-governance adoption, and micro-level studies assessing the return on investment of data-quality interventions and interpretive training. Such research would further clarify how human-centric AI architectures influence productivity, trust, and resilience in labour markets under conditions of digital asymmetry.

The OECD evidence (2025) underscores the urgency of this agenda: delayed AI adoption increases economic vulnerability, particularly in SME-dominated economies with fragmented digital infrastructures. Firms lacking robust data governance face elevated risks of algorithmic bias, cybersecurity incidents, and technological lock-in. The capacity to manage AI responsibly and

interpretively will therefore be decisive in determining which organisations and regions translate HR 5.0 principles into a long-term competitive advantage.

In conclusion, the AI divide in HR is not a deterministic outcome of technological inequality, but a strategic choice shaped by architecture, competence, and governance. Organisations that position AI as a partner—rather than a substitute—are more likely to build human-centric, trustworthy, and productive HR ecosystems in the digital economy.

Use of Artificial Intelligence (AI) or AI-based Tools: *During the preparation of this manuscript, the author used ChatGPT for language editing and stylistic refinement of the text. After using this tool, the author reviewed and edited the content as necessary and takes full responsibility for the content of the published article.*

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The Digital Divide among Vulnerable Groups in the Second and Third Phases of the Latest EU Enlargement Generation

Preliminary communication

Đorđe Mitrović[1], Đorđe Kotarac[2]

ABSTRACT

The emphasis on the exogenous nature of technological progress, as a significant determinant of economic development in the early 20th century, led to the emergence of the endogenous growth theory. According to the endogenous model, long-term growth depends on research and development activities in the ICT sector, coupled with improvements in education to cultivate human capital as the carrier of digital progress. During the second and third phases of the latest EU enlargement generation, candidate countries were required to fulfil the Copenhagen criteria, with special attention given to Chapters 10 (Information Society and Media), 20 (Enterprise and Industrial Policy), 25 (Science and Research), and 26 (Education and Culture). Beyond financial benefits, countries adopted a range of EU regulations, directives, and strategies that contributed to digital development and reduction in the digital divide among vulnerable groups. Therefore, the research sample comprises countries from the second and third phases of the latest EU enlargement generation. The study's methodology involves constructing three sub-indices: internet usage, digital skills, and access to digital devices – that collectively form the Digital Divide Index. The sub-indices based on data for vulnerable groups and the total population reflect a reduction in the digital divide within countries. The study's findings indicate progress in digital development and the mitigation of the digital divide among vulnerable groups in the second and third phases of the latest EU enlargement countries. Specifically, countries such as Romania, Bulgaria and Croatia harmonised their legislation with EU standards, reducing the digital divide and closing the gap in relation to vulnerable groups in other EU states.

***Keywords**: Digital divide, Vulnerable groups, Endogenous growth theory, DIDIX Index*

1 *Full professor, University of Belgrade, Faculty of Economics and Business, Kamenička 6, 11000, Belgrade, Serbia. Scientific affiliation: Economics. Phone: +38163217348. E-mail: dorde.mitrovic@ekof.bg.ac.rs*

2 *Teaching Assistant, University of Belgrade, Department of Economics, Faculty of Agriculture, Nemanjina 6, 11 000, Belgrade, Serbia, Scientific affiliation: Economics. Phone: +381616730760. E-mail: djordje.kotarac@agrif.bg.ac.rs*

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1 Introduction

Within the framework of the European Union member states' economic policies, digital development and the activities of the ICT sector have been recognised as one of the key determinants of long-term economic growth. Research and development in technical and technological innovation contribute to the optimisation of operational processes, thereby enhancing productivity (Diermeier & Goecke, 2017). The unlimited nature of innovation processes drives continuous technological advancement, fostering thus long-term economic growth (Broughel & Thierer, 2019). The endogenous growth theory identifies technological progress, along with the development and application of digital technologies, as one of the key factors driving economic development (Howitt, 2018). However, the endogenous growth theory has not provided an adequate explanation for the differences in growth rates observed among countries (Chirwa & Odhiambo, 2018). This phenomenon is linked to the process of technological diffusion from leading to follower economies. Digitally less advanced countries, which are often economically less developed, adopt technological innovations and production methods from digitally more advanced nations (World Economic Forum, 2015). Less developed countries allocate limited resources to R&D, relying on imitation to attain higher returns on capital, thereby converging with advanced economies (Barro, 2015). Technological advancement and digital development, subsequently embedded in the legal framework and EU accession criteria, play a critical role in shaping the digital readiness of countries seeking EU membership (European Commission, 2020).

The European Union enlargement process is primarily based on the fulfilment of the so-called "Copenhagen criteria", which were adopted by the European Council on 21-22 June 1993 (European Commission, 2020). According to this document, the conditions for EU accession can be categorised into three groups of criteria: political, economic, and institutional (European Council, 1993). The first group encompasses democracy, the rule of law, human rights, and the protection of national minorities. The second group comprises a functioning market economy and the capacity of market actors. The third group pertains to the alignment with and adoption of the EU legal framework ("acquis communautaire"). Notably, the original "Copenhagen criteria" did not cover digital development or ICT advancement. Recognising the role of digital technologies in economic development, EU policymakers expanded the third criteria group through initiatives such as the "Digital Single Market" (2015), the "Digital Agenda for Europe" (2010-2020), and the "Digital Compass" (2030) (European Commission, 2010, 2015, 2021). The EU accession criteria, originally established amid limited digital development, were subsequently revised to incorporate the assessment of a candidate country's digital readiness (European Parliament and Council of the European Union, 2024).

The evaluation of the digital maturity of candidates and prospective EU member states is embedded in Chapter 10 – "Information and Society and Media". Within the digital economy, this chapter focuses on removing

barriers in telecommunication and online services, fostering competition in the communications sector, safeguarding consumer data, and ensuring universal access to digital technologies (European Commission, 2023a). The demand for digital transformation is emphasised in Chapter 20 – "Entrepreneurship and Industrial Policy". The chapter prioritises increasing labour productivity through the application of digital technologies in production processes, with digital innovation primarily targeting the SME sector (European Commission, 2023b). Digital literacy and skills are addressed in Chapter 25 – "Science and Research". The focus is on developing human, institutional, and financial capacities to participate in European Union research programs, such as "Horizon 2020", and "Horizon Europe 2021-2027" (European Commission, 2023c).

The development of digital technologies is a key component of Chapter 26 – "Education and Culture". This chapter emphasises the role of human capital as the primary driver of technological progress. Among various European Union directives, regulations, and strategies, the "European Education Area" (2025) initiative is particularly notable, including its "Digital Education Plan" (2021-2027). These documents highlight the need for digital education, the development of students' digital competencies, and the greater integration of technological innovation in education (European Commission, 2023d). The evolved Copenhagen criteria emphasise that, beyond digital development, reducing the digital divide among vulnerable groups in candidate populations is equally critical (European Parliament and Council of the European Union, 2024). Based on the foregoing, the research question serves as the primary motivation for this research:

Following the adoption and implementation of the evolved Copenhagen criteria, second- and third-wave countries from the latest EU enlargement have continuously been reducing the digital divide between vulnerable groups and the general population.

By fulfilling the revised Copenhagen criteria, second- and third-wave EU candidate countries continue to advance their digital development to mitigate the digital divide across their population. This study examines the digital maturity of these countries and the adoption of digital technologies by vulnerable groups relative to the population in the post-accession period.

2 Literature review

According to the World Bank (2016), the diffusion of digital technologies spans most countries worldwide. Yet, the implementation of imported technological innovations and the reduction of the digital divide within populations in developing countries remain limited. Similarly, the World Economic Forum (2015) notes that less developed countries are constrained by their fundamental characteristics, failing to leverage ICT potential for social and economic transformation, and consequently, not closing the digital divide both internationally and within population cohorts. Therefore, the demand for further economic development is closely linked to the reduction in the digital divide between vulnerable groups and general population (Rogers, 2016). According to Adkins and Sandy (2020), one such vulnerable group, evident across

most countries, comprises female individuals. Reduced utilisation of digital technologies and digital skills among women (Acilar et al., 2023) is particularly pronounced in rural areas (Cortelyou-Ward et al., 2020) and among national minorities (Bartikowski et al., 2018). According to Lin et al. (2017), segments of the population with lower income levels tend to use digital technologies less frequently. This argument is further supported by Helsper and Reisdorf (2017), who confirm that segments of the population with lower income levels have fewer opportunities to access and utilise ICTs. Similarly, Olphert et al. (2013), emphasise that older population groups face significant constraints in developing digital skills and knowledge. Matthews et al. (2019) demonstrate lower level of digital technology use among individuals aged 50 and older. Owing to limited motivation to acquire digital skills later in life, this vulnerable group lags behind the general population in digital technology use (Wu et al., 2015). The last vulnerable group comprises individuals with no or low levels of basic education (Elena-Bucea, 2021). Lower educational attainment is strongly linked to the digital divide within the population (Lythreatis et al., 2022). The European Commission (2020) emphasises the need to narrow the digital divide between vulnerable groups and the entire population in EU candidate countries. The expanded Copenhagen criteria underscore the importance of aligning the digital development of EU candidate countries with EU standards (European Council, 1993). Furthermore, countries that have joined the EU tend to advance in ICT adoption, thereby reducing the digital divide relative to other EU member states (OECD, 2021).

3 Methodology and conceptual framework

To measure the digital divide between vulnerable groups relative to the overall population of countries, a Digital Divide Index, abbreviated as the “DIDIX Index”, has been developed. The composite nature of this index, which includes multiple individual indicators, makes it a robust tool for assessing the digital divide within the populations of the observed units. The Digital Divide Index represents the ratio between indicators of digital technology use within specific vulnerable groups and indicators of digital technology adoption across the overall population (Vehovar et al., 2006).

To construct the Digital Divide Index, four socio-demographic factors are examined in relation to three individual indicators of digital development, capturing both the societal conditions and the overall economic context of each county. The socio-demographic factors assess the adoption and use of digital technologies with respect to gender, age group, education level, and the material wealth of the population in the given countries. In contrast, the three sub-indicators of a country’s digital development measure the availability of modern digital devices and internet connectivity; the capacity to gather information and purchase goods and services through contemporary e-commerce channels; and the set of skills and knowledge required to operate digital devices and use digital technology effectively (Husing & Selhofer, 2004).

The construction of the Digital Divide Index (DIDIX) is based on the following elements:

1. The percentage of the total population that uses the internet and regularly consumes digital content.
2. The percentage of the population that gathers information and purchases goods and services through electronic sales channels.
3. The percentage of the population that possesses basic or at least minimal digital skills necessary for the use of digital devices and contemporary technological tools.

After calculating the three sub-indicators related to the level of digital economy development, four distinct vulnerable groups are identified:

1. The proportion of the older residents, aged 55 to 74.
2. The proportion of female residents, aged 16 to 74.
3. The proportion of residents with no formal education or only basic education.
4. The proportion of residents without stable employment, classified as unemployed.

For the purposes of calculating the Digital Divide Index (DIDIX), the following formula is used:

$$DDI = \frac{1}{n}\sum_{i=1}^{n} Di \qquad (1)$$

where Di denotes the value of the individual sub-indices for each of the four observed vulnerable groups (i), within the total population of the countries under analysis. Accordingly, the calculation of the composite Digital Divide Index (DIDIX) is preceded by the computing of the three sub-index values, as presented in Table 1.

Table 1: Assigned sub-indicators weights for the calculation of the composite DIDIX Index

Country (n)	Sub-Index A		Sub-Index B		Sub-Index C		Sub-Index Weight*
Time Period	Number of internet users		Information about products / services via digital devices		Development of digital skills		
Total Usage	(%)	(%) of total population	(%)	(%) of total population	(%)	(%) of total population	
Age	S_{1A}	S_{11A}	S_{1B}	S_{12B}	S_{1C}	S_{13C}	0.5 * S_{ijA}
Gender	S_{2A}	S_{21A}	S_{2B}	S_{22B}	S_{2C}	S_{23C}	+
Education	S_{3A}	S_{31A}	S_{3B}	S_{32B}	S_{3C}	S_{33C}	0.25* S_{ijB} +
Low income (unemployment)	S_{4A}	S_{41A}	S_{4B}	S_{42B}	S_{4C}	S_{43C}	0.25* S_{ijC}
Sub-index	S_{iA}	S_{ijA}	S_{iB}	S_{ijB}	S_{iC}	S_{ijC}	DIDIX (DDI)

Source: Hüsing, T., Selhofer, H. (2004)

Through the assignment of weights to each of the three sub-indices (Number

of internet users, Information about products/services via digital devices, Development of digital skills), a composite Digital Divide Index (DIDIX INDEX), is calculated. The following formula is applied to compute the value of each of the three sub-indices:

$$Di = 100 * \sum_{j=1}^{m} Wj * \frac{Sij}{Sj} \tag{2}$$

where the notation Wj denotes the assigned weight of indicator (j) $(j = 1,2,3, Sw = 1)$, Sij represents the value of indicator (j) for each vulnerable group (i) $(i = 1,2,3,4)$, while Sj denotes the value of the sub-indicator (j) for the total population (Hüsing and Selhofer, 2004).

The composite Digital Divide Index (DIDIX) measures digital technology adoption among vulnerable groups relative to the total population. If the adoption of digital technologies by a vulnerable group is equal to that of the total population, the index will equal 100. Therefore, a Digital Divide index value closer to 100 indicates a smaller digital divide within the population (Vehovar et al., 2006).

In order to calculate the composite index, it is necessary to determine the appropriate weights. The weights are determined endogenously, that is, through Data Envelopment Analysis (DEA) by applying linear programming techniques (Hüsing & Selhofer, 2004; Mitrović, 2020; Kotarac et al., 2025) This procedure ensures the maximisation of the composite index value while guaranteeing that no alternative combination of weights could yield a higher index value (Vehovar et al., 2006).

The research sample includes countries from the second and third waves of the latest EU enlargement. The data for the empirical analysis were sourced from Eurostat (2015-2023), specifically from the Science, Technology, and Digital Society database. As for the comparative analysis, the digital divide index was calculated for the EU-27 average, and for Estonia and Finland, the benchmark leaders in digital economy development. The research covers 2015-2023 period, following the third wave of the latest EU enlargement, which is the most recent year with publicly available data.

4 Results and discussion

The results of the methodological part of this research are provided by measuring the extent of the digital divide in countries that joined the European Union during the second and third waves of the latest EU enlargement. This approach allows for a comparison with the average prevalence of the digital divide within the EU-27 countries (Table 1). By calculating the composite Digital Divide Index, a series of conclusions are drawn regarding the extent of the digital divide between vulnerable groups and the overall population of the new EU-27 member states, relative to the selected reference points. The reference countries are EU-27 members exhibiting the highest levels of digital development, digital transformation, and ICT access. Based on the DDI Index

(ITU, 2023-2025), Estonia and Finland were selected as reference countries (Table 2). The Digital Divide Index results therefore serve as a foundation for drawing conclusions on how to address the digital divide in the observed countries.

Table 2: Calculation of the Digital Divide Index ("DIDIX")

Country	**CROATIA – third wave of the latest EU enlargement**			**1**
	Sub-Index 1	**Sub-Index 2**	**Sub-Index 3**	**(u1+u2+u3)**
Time Period (t)	**Individuals' frequency of internet use**	**Individuals' online product purchases and information**	**Digital skills of individuals**	**Index Value**
2015	0.3501	0.1859	0.1557	69.2
2017	0.3497	0.1994	0.1504	69.9
2019	0.3846	0.1897	0.1463	72.1
2021	0.4056	0.1831	0.1656	75.4
2023	0.4126	0.2005	0.1714	78.4
Country	**BULGARIA - second wave of the latest EU enlargement**			**2**
2015	0.3793	0.1690	0.1316	67.9
2017	0.3947	0.1660	0.1361	69.7
2019	0.3982	0.1673	0.1289	69.4
2021	0.4474	0.1702	0.1390	75.7
2023	0.4503	0.1850	0.1567	79.2
Country	**ROMANIA - second wave of the latest EU enlargement**			**3**
2015	0.3757	0.1760	0.1659	71.8
2017	0.3996	0.1619	0.1585	72.0
2019	0.4158	0.1793	0.1694	76.4
2021	0.4301	0.1799	0.1619	77.2
2023	0.4542	0.2030	0.1687	82.6
Countries	**EUROPEAN UNION COUNTRIES (27)**			**Average value**
2015	0.4112	0.2008	0.1805	79.2
2017	0.4240	0.2040	0.1800	80.8
2019	0.4400	0.2070	0.1820	82.9
2021	0.4567	0.2142	0.1936	86.5
2023	0.4722	0.2131	0.1930	87.8

Source: Authors

Based on the results in Table 1, the digital divide among four vulnerable groups is highlighted relative to the total population of the EU-27 new member states. Following delays in meeting the Copenhagen criteria during the

second wave of the latest EU enlargement, Romania and Bulgaria joined the EU on 1 January 2007, marking their entry into the European digital economy. The 2015 digital divide index indicates that Bulgaria's vulnerable groups used digital technologies at a level below 7/10 of the total population. By 2023, this gap had narrowed, with usage exceeding 7/10 and approaching 8/10 of the overall population. By contrast, Romania initially exhibited a lower level of digital divide between vulnerable groups and the overall population, with digital technology usage among vulnerable groups exceeding 7/10 of the total population's level. This trend of reducing the digital divide continued in the years following Romania's EU accession, reaching 2023, when digital technology usage among vulnerable groups exceeded 8/10 of the overall population. Following the longest-ever EU accession negotiations, Croatia became a member on 1 July 2013. According to the composite digital divide index, two years after accession, vulnerable groups in Croatia used digital technologies at less than 7/10 of the level observed in the overall population. However, EU accession provided Croatia with further opportunities to reduce the digital divide through infrastructure investment, education, and digitalisation of services. In 2023, digital technology usage among vulnerable groups in Croatia exceeded 7/10 of the total population. The following selection presents the calculated digital divide index (DIDIX), values for two benchmarks, selected for their leading positions in digital development according to the International Telecommunication Union's DDI index. These measurements, covering the period from 2023 to 2025, enable a comparison of the digital divide across the most digitally advanced nations.

Table 3: DIDIX (Digital Divide Index) values for two reference EU-27 countries

Country	**FINLAND**			**Reper 2**
	Sub-Index 1	**Sub-Index 2**	**Sub-Index 3**	**(u1+u2+u3)**
Time Period (t)	**Individuals' frequency of internet use**	**Individuals' online product purchases and information**	**Digital skills of individuals**	**Index Value**
2015	0.4709	0.2253	0.2170	91.3
2017	0.4719	0.2216	0.2214	91.5
2019	0.4748	0.2134	0.2252	91.3
2021	0.4853	0.2275	0.2268	93.9
2023	0.4862	0.2210	0.2357	94.3
Country	**ESTONIA**			**Reper 2**
	Sub-Index 1	**Sub-Index 2**	**Sub-Index 3**	**(u1+u2+u3)**
Time Period (t)	**Individuals' frequency of internet use**	**Individuals' online product purchases and information**	**Digital skills of individuals**	**Index Value**
2015	0.4348	0.1969	0.1923	82.4

2017	0.4653	0.2133	0.2075	88.6
2019	0.4694	0.2238	0.2088	90.2
2021	0.4776	0.2263	0.2107	91.4
2023	0.4831	0.2291	0.2109	92.3

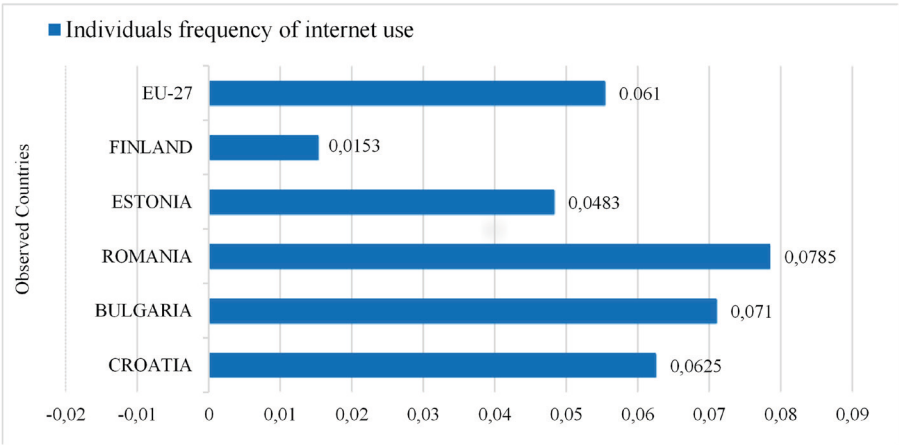
Source: Authors' calculation, based on the Eurostat data.

To compare the extent of the reduction in the digital technology usage gap among vulnerable groups within the populations of second-wave and third-wave countries of the latest EU enlargement, the digital divide index was calculated for the EU-27 average (Table 1). Additionally, the analysis was extended by calculating the digital divide index for two benchmark countries exhibiting the highest levels of digital development, namely Estonia and Finland (Table 2). In 2015, the average use of digital technologies across different cohorts within the populations of the EU-27 countries was calculated, revealing that vulnerable groups used digital technologies at less than 8/10 of the level observed in the overall population. Progress in reducing the digital divide was confirmed by the calculation of the digital divide index for 2023. Specifically, digital technology usage among vulnerable groups was measured at a significantly higher level, exceeding 8/10 of the total population's usage in the respective countries.

The first benchmark country is Finland, which became a full-fledged member of the European Union in May 1995. According to the digital divide index results (Table 2), in 2015, vulnerable groups used digital technologies at more than 9/10 of the level observed in the total population. This trend was confirmed in 2023, when vulnerable groups continued to use digital technologies at over 9/10 of the total population's usage in Finland. The second benchmark country is Estonia, which became a full-fledged member of the European Union on 1 May 2004. In 2015, the calculated level of digital technology usage among vulnerable groups in Estonia was slightly above 8/10 of the total population's usage. Over the past two decades, Estonia has successfully reduced the digital divide, as reflected in the index's values. By 2023, vulnerable groups in Estonia had been using digital technologies at a slightly over 9/10 of the level observed in the total population.

The following presents a graphical representation of the changes in the index values of each of the three sub-indicators that constitute the composite digital divide index (DIDIX). The analysis begins with the first sub-indicator, which measures individuals' frequency of internet use.

Figure 1: Change in the first sub-indicator of the digital divide index (2015-2023)

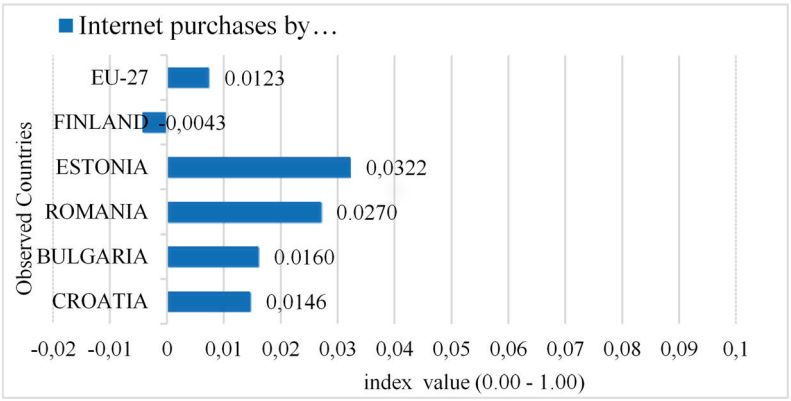


Source: Authors

The first sub-indicator of the digital divide index reflects the frequency of internet use among individuals within the populations of the EU-27 countries. The data measures the number of daily internet users. Eurostat's database allows for the analysis of this indicator across different vulnerable groups within a country's population.

An upward movement in this sub-index indicates more advanced digital infrastructure and reduced barriers to Internet access, thereby reflecting progress toward higher levels of digital inclusion within the population. The analysis examines how the total number of internet users evolved among countries from the second and third waves of the EU-27 enlargement, with a focus on vulnerable population groups. The largest increase in internet users was recorded in Romania, corresponding to a 7.85-point increase in the first sub-index. Countries such as Bulgaria, Romania, and Croatia recorded higher growth in internet usage than the EU-27 average, with an increase of 6.10 points in the sub-index measuring the level of digital inclusion among the population.

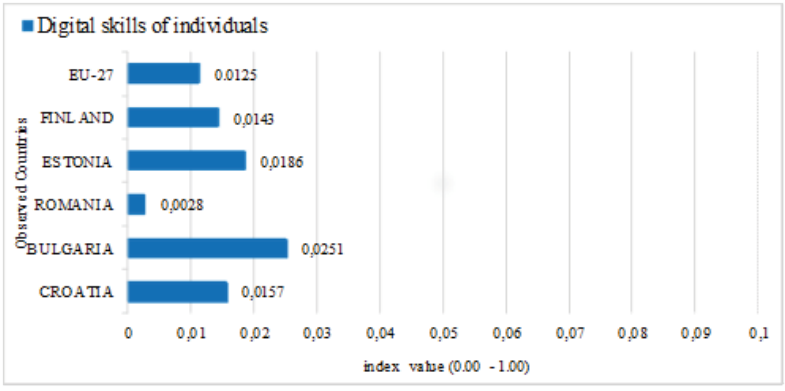
Figure 2: Change in the second sub-indicator of the digital divide index (2015-2023)



Source: Authors

The second sub-indicator captures the proportion of the population that had used the internet to obtain information and for purchasing goods or services. To assess the engagement with electronic commerce channels, this indicator measures total visits and completed transactions over the previous 12 months across retail and wholesale platforms. Between 2015 and 2023, Romania recorded the highest growth in users of electronic sales channels, with an increase of 2.7 index points. Furthermore, countries from the second and third waves of the latest EU-27 enlargement had a higher proportion of internet users engaged in online information retrieval and purchases than the EU-27 average.

Figure 3: Change in the third sub-indicator of the digital divide index (2015-2023)



Source: Authors

The third sub-indicator assesses the development of digital skills within a population. Specifically, this sub-indicator reflects the extent to which a country's population possesses the digital competencies required to operate modern digital devices and utilise internet-based content effectively. Enhancing the population's digital skills has become a prerequisite for further implementation of advanced technological innovations, with human capital serving as the key driver of a country's digital progress. Between 2015 and 2023, all countries in the second and third waves of the most recent EU enlargement experienced measurable growth in their populations' digital competencies. Among these countries, Bulgaria recorded the largest increase in digital competencies, rising by 2.51 index points. Croatia exceeded the EU average, with an increase of 1.51 index points in digital competencies, while Romania recorded a modest rise of approximately 0.30 index points.

Table 3 presents the analysis of changes in each of the three sub-indices that constitute the composite DIDIX index, examined individually for vulnerable groups.

Table 3: Analysis of changes in digital divide within vulnerable groups (2015-2023)

Country 1	**CROATIA**		
Vulnerable groups	**Individuals' frequency of internet use**	**Individuals' online product purchases and information**	**Digital skills of individuals**
K1	+24.43%	+24.91%	+10.04%
K2	+18.20%	+31.33%	+11.58%
K3	+21.10%	+23.08%	+8.81%
K4	+24.31%	+14.32%	+4.39%
Country 2	**BULGARIA**		
K1	+28.96%	+17.58%	+6.49%
K2	+25.23%	+25.17%	+4.81%
K3	+33.10%	+11.77%	+3.73%
K4	+34.65%	+22.00%	+8.30%
Country 3	**ROMANIA**		
K1	+53.63%	+22.18%	+3.11%
K2	+37.93%	+39.82%	+1.81%
K3	+46.91%	+24.91%	-0.03%
K4	+25.82%	+42.71%	+0.20%
Country R1	**ESTONIA**		
K1	+18.09%	+14.19%	+4.55%
K2	+8.88%	+11.69%	-1.76%

K3	+20.72%	+15.93%	+10.86%
K4	+10.46%	+36.14	-0.86%
Country R2	**FINLAND**		
K1	+14.00%	+12.27%	+10.84%
K2	+5.68%	+6.67%	+9.12%
K3	+10.75%	+4.16%	+16.98%
K4	+1.65%	-6.02%	+15.52%
Countries R3	**EUROPEAN UNION (27) AVERAGE**		
K1	+31.57%	+10.88%	+8.11%
K2	+17.36%	14.69%	+3.46%
K3	+27.72%	+11.58%	+2.91%
K4	+17.89%	+16.48%	+2.22%

Source: Authors

The results presented in Table 4 provide insights into the percentage change in all three sub-indicators of digital technology adoption across each vulnerable group, examined through different units of observation. The findings indicate which vulnerable group, and to what extent, contributes to digital convergence or divergence in relation to the overall population. In the case of Romania, the greatest contribution to digital convergence was made by the first vulnerable group, referring to individuals aged 55-74. This group accounted for the largest share in the increase of internet users (54.63%) and in the development of digital skills (3.11%). The growth in online purchasing and information-seeking via e-commerce channels was primarily driven by the fourth vulnerable group (42.71%). In the case of Bulgaria, the fourth vulnerable group achieved the greatest increase in digital skills (8.20%) and the number of internet users (34.65%). The second vulnerable group, comprising women aged 16-74, contributed most significantly to online purchasing and information-seeking through e-commerce channels (27.17%). In Croatia the second vulnerable group, comprising women aged 16-74, made the greatest contribution to digital convergence, with the largest share in online purchasing and information-seeking (31.33%) and in digital skills development (11.58%). However, the first vulnerable group, individuals aged 55-74, experienced the largest increase in internet users (24.43%).

An analysis of vulnerable groups' contribution to digital convergence in two benchmark countries highlights the key role of the third group, comprising individuals with low or no formal education. In Estonia, the third vulnerable group made the most significant contribution to reducing the digital divide, with the largest increases in internet users (20.72%) and digital skills (10.85%). The fourth vulnerable group, comprising the unemployed, achieved the largest share in the growth of online purchasing and information-seeking through e-commerce channels (36.14%). In Finland, the third vulnerable group achieved the greatest contribution to reducing the digital divide, with the largest gain in internet users (10.75%) and digital skills (16.98%). The first

vulnerable group had the largest share in online purchasing and e-commerce information-seeking (12.27%).

Table 4: Change in the composite DIDIX index (2015-2023)

TIME PERIOD	COUNTRIES	DIDIX INDEX (2023)	DIDIX INDEX CHANGE
2015-2023	CROATIA	78.4	*ΔDIDIX index = 9.20*
2015-2023	BULGARIA	79.2	*ΔDIDIX index = 11.30*
2015-2023	ROMANIA	82.6	*ΔDIDIX index = 10.80*
2015-2023	ESTONIA	92.3	*ΔDIDIX index = 9.90*
2015-2023	FINLAND	94.3	*ΔDIDIX index = 3.00*
2015-2023	EUROPEAN UNION (27)	87.2	*ΔDIDIX index = 8.60*

Source: Authors' calculation, based on the Eurostat data.

According to the results in Table 4, two countries from the second wave of the latest EU enlargement achieved a higher degree of digital convergence of vulnerable groups relative to the overall population, compared to one country from the third wave of the latest EU enlargement. Between 2015 and 2023, Bulgaria reduced the level of digital divide by 11.30 index points. Over the same period, Romania achieved a reduction of 10.80 index points. In the third wave of the latest EU enlargement, Croatia reduced the digital divide by 9.20 index points. Thus, it is evident that countries from the second and third waves of the latest EU enlargement had reduced the digital divide between vulnerable groups and the overall population, exceeding the EU-27 average reduction of 8.60 index points. In this sense, these countries had been digitally catching up with the EU-27 through greater reductions in the digital divide and advances in digital development.

5 Conclusions

In the process of accession to the European Union, candidate countries are required to satisfy three categories of criteria, as established and adopted by the European Council in Copenhagen in 1993. With the advent of technological progress and contemporary digital innovations at the end of the 20th century, objectives related to the digital transformation of countries have become an integral part of the negotiation chapters for European Union accession. Furthermore, the alignment of policies and legal frameworks following accession to the European Union ensures continued advancement of digital development in the new member states. However, the advancement of digital development must be accompanied by a reduction in the digital divide within these countries' populations. In this context, full European Union member states aim to shape their national strategies and economic policies not only to achieve economic growth but also to reduce the digital divide across different population cohorts. The analysis indicates that the countries

of the second and third waves of the latest European Union enlargement have significantly reduced the digital divide between vulnerable groups and the overall population. Furthermore, through alignment with the European Union standards and regulations, the new member states are advancing toward the average level of digital development of European Union countries.

The research concludes that the digital divide between vulnerable groups and the overall population is smallest in the countries with the longest European Union membership. The lowest digital divide was observed in Finland, which acceded to the European Union in January 1995, and in Estonia, which became a full member in May 2004. Subsequently, a slightly higher digital divide was observed in Romania and Bulgaria, which acceded to the European Union in January 2007. Finally, the most pronounced digital divide was measured in Croatia, which joined the European Union in July 2013. Countries that joined the European Union earlier had gained access to structural and cohesion funds in order to develop their digital infrastructure, enhance the education system, and promote technological innovation. The reduction of the digital divide among European Union member states is achieved through investment in digital literacy, engagement of the private sector in the digital economy, and strengthening of institutions responsible for implementing national and digital transformation policies.

Within the framework of national strategy measures and economic policy objectives, increasing emphasis is placed on promoting economic development, while simultaneously enhancing digital inclusion and reducing the digital divide within the population. However, a negative correlation is often observed between technological progress and the digital divide that emerges among different population cohorts. This is primarily due to limited access to digital technologies among all economic actors. At the same times, the lack of skills required to implement technological advancements further widens the digital divide within specific populations. In this context, the pursuit of economic development objectives is closely linked to achieving digital equality with a population. Reducing the digital divide between vulnerable groups and the general population fosters greater digital inclusion and technological progress, ultimately contributing to higher levels of economic development and societal well-being.

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Digital Tax Administration Performance: Regulatory Quality in EU and MENA countries

Original scientific paper

Berbache Sami[1]

ABSTRACT

This study examines the relationship between regulatory quality and e-government development across 21 countries in 2022, focusing on the performance gap between EU and MENA regions. Using cross-sectional regression analysis, we investigate whether regulatory quality—the government's ability to formulate sound policies—explains digital government performance beyond economic development and ICT infrastructure. Data from UN E-Government Survey, World Bank Worldwide Governance Indicators, and ITU sources reveal substantial regional disparities: EU countries average EGDI 0.916 while MENA countries average 0.692. Slovenia (EGDI 0.854, 84th regulatory percentile) significantly outperforms Algeria (EGDI 0.607, 28th percentile) despite comparable internet penetration. Multivariate regression controlling for GDP, internet access, government effectiveness, and corruption shows that regulatory quality maintains strong positive association with EGDI (β=0.0023, $p<0.001$, R^2=0.966). EU membership shows no additional effect beyond national regulatory quality. Results suggest that regulatory quality enables effective technology utilization: countries with strong regulatory frameworks achieve higher digital government performance from equivalent infrastructure investments. Policy implications indicate that MENA countries may achieve greater returns from institutional reforms—interoperability standards, data protection frameworks, technology-neutral regulations—than from infrastructure spending alone. The study contributes empirical evidence that institutional quality, not merely technological capacity, determines digital transformation outcomes.

Keywords: *Digital tax administration, Regulatory quality, E-government, Digital transformation, MENA development*

JEL classification: *H20, H83, O33, O38, O57*

1 *PhD Candidate, University of Ljubljana, Faculty of Public Administration, Kongresni trg 12, 1000 Ljubljana, Slovenia. Scientific affiliation: Joint Doctoral Program in Governance and Economics in the Public Sector. Phone: +213 669 517 278. E-mail: sb05581@student.uni-lj.si.*

1 Introduction

Digital transformation in tax administration represents a critical component of modern government operations, with implications for revenue collection efficiency, compliance costs, and state-citizen relationships (Twizeyimana & Andersson, 2019). Global tax revenues exceed $15 trillion annually, and administrative costs typically consume 0.5-2% of total collections, creating substantial efficiency gains from digitalization (OECD, 2020). Advanced economies realized these gains rapidly: Denmark achieved 99.5% e-filing rates by 2020, Estonia integrated tax systems with digital identity infrastructure enabling automated return pre-filling, and Singapore reduced business compliance burdens by 40% through digital platforms (Lember et al., 2019; Alm & Soled, 2017). However, developing countries face significant implementation challenges despite substantial infrastructure investments, with e-filing adoption remaining below 30% in many middle-income countries and digital service quality lagging substantially behind technological capacity (Savoldelli et al., 2014).

Cross-national evidence reveals persistent performance disparities in digital government development that correlate with, but are not fully explained by, economic or infrastructural differences. The UN E-Government Development Index (EGDI) shows European Union countries averaging 0.85-0.90 while Middle East and North Africa (MENA) countries average 0.65-0.70, representing a 25-30% performance gap (United Nations, 2024). These gaps persist despite comparable internet penetration rates and substantial digital infrastructure investments in middle-income MENA countries. Recent panel studies demonstrate that governance quality indicators—particularly regulatory quality and government effectiveness—explain significant variance in e-government outcomes beyond economic and technological factors (Inusah et al., 2024; Seiam & Salman, 2024). However, the specific marginal effect of regulatory quality independent of general administrative capacity remains underexplored. This gap is particularly important because regulatory quality represents a more actionable policy lever than broad governance reform. Moreover, whether regional harmonization frameworks such as the European Union provide performance benefits beyond national institutional quality had not been empirically tested with adequate controls (Gil-Garcia et al., 2020). Comparative EU-MENA studies rarely isolate EU membership effects from national governance characteristics, leaving unclear whether regional frameworks add value beyond countries' own institutional quality.

Existing research establishes strong associations between governance quality and digital government performance but faces two limitations. First, most studies employ governance indicators as undifferentiated composite measures, limiting understanding of which specific institutional dimensions matter most for digital transformation (Wirtz & Müller, 2019). Second, comparative EU-MENA studies rarely control simultaneously for economic development, infrastructure, and multiple governance dimensions, leaving uncertainty about whether observed performance differences reflect regulatory quality specifically or confounding factors (Bannister & Connolly, 2014). This study addresses these gaps by examining the relationship between regulatory quality and digital government performance measured by EGDI, controlling

for GDP per capita, internet penetration, government effectiveness, and corruption levels. The analysis employs cross-sectional regression with 21 countries in 2022, providing statistical power to detect regulatory quality effects while enabling focused comparison between Slovenia (EU context) and Algeria (MENA context) as representative cases.

This study examines the relationship between regulatory quality and digital government performance as measured by the E-Government Development Index (EGDI). Thus, it seeks to answer two central research questions: first, how regulatory quality influences EGDI outcomes, and second, whether membership in harmonized regional frameworks—specifically the European Union—yields performance benefits that extend beyond the effects of regulatory quality alone. Based on these questions, the study proposes two hypotheses. The first posits that higher levels of regulatory quality are positively associated with EGDI scores, even when controlling for key contextual variables such as GDP, internet penetration, and government effectiveness. The second hypothesis suggests that countries operating within harmonized institutional frameworks, such as the EU, exhibit higher EGDI performance that cannot be explained solely by regulatory quality, indicating an added value of regional alignment and shared standards.

The remainder of this paper is organized as follows. Section 2 reviews the literature on digital government development, institutional determinants of e-government performance, and EU harmonization frameworks, establishing the theoretical foundation for the empirical analysis. Section 3 describes the research design, data sources, and analytical strategy, including variable operationalization and model specification. Section 4 presents the empirical data and sample composition. Section 5 reports results from descriptive analysis, correlation analysis, and multivariate regression models, followed by discussion of findings in relation to the Slovenia-Algeria comparison and broader policy implications. Section 6 concludes with hypothesis assessment, contributions to economic science, research limitations, future research directions, and institutional-systemic policy recommendations.

2 Literature review

2.1 Measuring e-government development

Research on digital government development relies primarily on the United Nations' E-Government Development Index (EGDI) as the standard cross-national metric for comparing digital government capacity and output (United Nations, 2024). The UN E-Government Survey and its EGDI provide the most comprehensive global benchmark, capturing three dimensions relevant to digital government capacity: online service provision, telecommunications infrastructure, and human capital. The global EGDI average increased from 61.02% to 63.82% between 2022 and 2024, with 71.5% of Member States recording high or very high EGDI levels, while the share of population lagging in digital government development fell from 45% in 2022 to 22.4% in 2024 (Seiam & Salman, 2024). The EGDI serves as our dependent variable because it captures the multidimensional nature of digital government capacity—combining technological infrastructure, human capital, and actual

service delivery—rather than focusing narrowly on single indicators such as website functionality or internet penetration alone.

Successive UN Survey editions and associated Member State questionnaires provide the most current cross-country EGDI scores and metadata, enabling researchers to track digital government evolution over time and identify performance determinants. The EGDI's composite structure—calculating the arithmetic mean of Online Service Index (OSI), Telecommunications Infrastructure Index (TII), and Human Capital Index (HCI)—ensures that high scores reflect balanced development across infrastructure, skills, and service delivery rather than excellence in a single dimension.

While EGDI effectively measures digital government supply-side capacity, understanding what drives variation in EGDI scores requires examining the institutional, economic, and infrastructural factors that enable or constrain digital transformation. We next address institutional determinants, particularly regulatory quality and broader governance dimensions examined further in the subsection below.

2.2 Institutional determinants: Regulatory quality and governance

Scholars studying institutional determinants of e-government have relied heavily on the Worldwide Governance Indicators (WGI)—particularly the Regulatory Quality and Government Effectiveness dimensions—because these indices operationalize state capacity and the quality of legal and regulatory frameworks that enable public-sector digitalization. The WGI framework is structured around six key governance dimensions: voice and accountability, political stability and absence of violence, government effectiveness, regulatory quality, rule of law, and control of corruption (Sultana, 2023). These dimensions, while conceptually distinct, capture overlapping aspects of institutional quality that jointly shape government performance.

Regulatory quality specifically measures perceptions of government ability to formulate and implement sound policies and regulations that permit and promote private sector development (Kaufmann et al., 2011). This dimension is conceptually distinct from government effectiveness, which captures perceptions of public service quality, policy implementation capacity, and bureaucratic competence. While government effectiveness emphasizes execution and administrative capability, regulatory quality focuses on the prior stage of policy design and the legal frameworks that structure both public and private sector activities. Control of corruption represents a third governance dimension, measuring perceptions of public power exercised for private gain and the extent to which corruption is controlled through institutional mechanisms.

The conceptual distinction between regulatory quality and government effectiveness matters both theoretically and practically. Regulatory quality represents a more upstream policy lever: governments can reform legal frameworks, establish interoperability standards, and adopt technology-neutral regulations through legislative and executive action. Government

effectiveness, in contrast, reflects deeply embedded administrative capacity that evolves more slowly through civil service professionalization, organizational restructuring, and cultural change. If regulatory quality independently predicts digital government performance beyond general administrative capacity, this suggests that institutional reforms targeting legal and regulatory frameworks may yield faster returns than comprehensive public sector reforms.

Empirical evidence on how regulatory quality and related institutional variables affect e-government is growing but nuanced. Recent cross-country and regional studies show that regulatory quality is positively associated with higher EGDI or e-government performance, often mediated or moderated by telecommunications infrastructure, digital skills, and government effectiveness. For example, Inusah et al. (2024) find that regulatory quality mediates the relationship between e-government development and government effectiveness, while mobile infrastructure contributes independently to e-government outcomes. This finding suggests that regulatory quality functions as a transmission mechanism: strong regulatory frameworks enable governments to translate general administrative capacity into effective digital services.

Sustainable improvements in government effectiveness emerge from robust control of corruption combined with high regulatory quality and strong accountability mechanisms (Abbas et al., 2023). Regulatory quality also has a positive and statistically significant impact on economic growth across countries (Seiam & Salman, 2024), indicating that a sound regulatory environment stimulates both economic performance and public-sector digitalization. These findings suggest that regulatory quality helps translate digital investments into improved public-sector performance—infrastructure alone is insufficient without enabling legal and regulatory frameworks.

However, the relationship is not uniformly positive across all contexts. Combining e-government platforms with strict regulations can show inverse relationships in contexts lacking institutional capacity, because effective digital governance requires proper institutional foundations (Abbas et al., 2023). This highlights the importance of regulatory quality rather than regulatory quantity: excessive or poorly designed regulations may constrain digital adoption even when well-intentioned. The literature thus emphasizes regulatory quality—the soundness and appropriateness of regulatory frameworks—rather than regulatory burden or stringency.

While governance quality clearly matters for digital government outcomes, existing research leaves two important questions unanswered. First, most studies employ governance indicators as composite measures or examine regulatory quality without controlling for government effectiveness and corruption simultaneously, leaving it uncertain whether regulatory quality matters independently or merely proxies for general institutional quality. Second, the literature demonstrates associations but provides limited evidence on the magnitude of regulatory quality effects or their practical significance for policy. We address these gaps by simultaneously controlling for multiple governance dimensions and quantifying effect sizes to inform policy prioritization. Beyond institutional quality, digital government development

requires economic resources and technological infrastructure. We examine these enabling factors next.

2.3 Economic and infrastructure enablers

While institutional quality shapes how effectively governments utilize technology, economic resources and ICT infrastructure determine what is technologically feasible. Economic development provides fiscal capacity for digital investments, correlates with human capital that facilitates technology adoption, and reflects broader modernization processes that generate the demand for digital services (United Nations, 2024). GDP per capita consistently correlates strongly with EGDI scores ($r = 0.70$-0.85 in most studies), suggesting wealthier countries achieve higher digital government performance through greater investment capacity, better skilled workforce, and stronger complementary infrastructure.

However, the GDP-EGDI relationship is not deterministic. Countries at similar income levels display substantial EGDI variance, indicating that economic resources are necessary but insufficient for digital transformation. Some middle-income countries achieve EGDI scores comparable to those of wealthier nations through strategic investments and strong institutional frameworks, while others, with similar GDP, underperform. This variance motivates examining institutional factors that enable countries to maximize returns on digital investments.

Telecommunications infrastructure, particularly internet penetration and broadband access, represents another necessary condition for e-government. Citizens cannot use online services without internet connectivity, and government agencies cannot deliver digital services without a reliable ICT infrastructure. International Telecommunication Union data show strong correlations between internet penetration rates and EGDI scores, with nearly universal internet access (>90%) in high-performing digital government countries.

Yet infrastructure alone is insufficient. Savoldelli et al. (2014) identify an "e-government paradox" in which developing countries face adoption barriers even after substantial infrastructure investments. Namely, citizens have internet access but do not use government digital services, and governments deploy online platforms that remain underutilized. This paradox suggests that the infrastructure creates potential for digital government, but institutional quality, trust, and service design determine whether that potential is realized. Countries can have widespread internet access and sophisticated digital platforms yet achieve poor EGDI scores if regulatory frameworks constrain interoperability, data protection concerns undermine trust, or the service design ignores user needs.

The infrastructure literature thus converges with institutional research in emphasizing complementarities: technology and institutions must co-evolve for an effective digital government. Infrastructure investments without supportive regulatory frameworks and administrative capacity yield limited returns, while strong institutions without adequate infrastructure face technological

constraints. This complementarity motivates our research design controlling for both infrastructure (internet penetration) and economic capacity (GDP per capita) when isolating regulatory quality effects. Only by holding infrastructure and resources constant can we identify institutional quality's independent contribution.

Infrastructure and institutions determine what governments can deliver digitally, but citizen adoption determines whether digital services achieve policy objectives. We examine adoption dynamics and citizen outcomes next.

2.4 Trust, adoption and citizen outcomes

Beyond supply-side metrics like EGDI, citizen adoption and the effects of e-government on governance outcomes depend critically on trust, perceived benefits, and digital divides. Research on citizen uptake highlights that higher technical performance does not automatically translate into greater citizen use. Differences in digital literacy, trust in government, and perceived service quality shape whether e-government produces governance benefits such as reduced corruption, increased transparency, and improved service delivery (Ma & Zheng, 2018; Pérez-Morote et al., 2020).

Trust emerges as an essential element when uncertainty or risk is present in e-government adoption: citizen confidence in both government and technology is an imperative for widespread voluntary adoption (Bélanger & Carter, 2008). Citizens must trust that the government will protect their data, that online services will function reliably, and that digital channels will not disadvantage them relative to traditional channels. Quality information provided by government agencies on social media improves perceived transparency and trust, which in turn increases citizen online participation (Albesher et al., 2016). Digital trust appears across governance, technology, and security domains as a persistent concern, with limited attention to trust-enhancing strategies in policy implementation (Kalesnikaite, 2023).

Regulatory frameworks directly shape this trust environment. Data protection legislation signals government commitment to privacy, and interoperability standards reduce citizen burden by enabling seamless service delivery across agencies, while technology-neutral regulations provide legal certainty that encourage citizen experimentation with digital channels. Thus regulatory quality may influence EGDI not only through enabling government service delivery but also by building the trust foundations necessary for citizen adoption.

The relationship between e-government and corruption has received substantial empirical attention, providing evidence that digital government can produce tangible governance improvements. Higher levels of e-government development, online service provision, human capital, and telecommunications infrastructure are associated with lower corruption perceptions in global panel analyses (Seiam & Salman, 2024). E-government reduces direct interaction between citizens and bureaucrats through online service delivery, limiting opportunities for extortion while maintaining transparent digital records (Shim & Eom, 2008).

E-government initiatives enhance transparency and accountability, which act as mediators between digital platforms and reductions in corruption (Abbas et al., 2023). Transparency improves more strongly when the UN e-government index (specifically online service provision and e-participation) is used as a proxy rather than simple freedom of information legislation (Kalesnikaite, 2023). Moreover, Mistry and Jalal (2012) demonstrate that e-government adoption reduces corruption by increasing transparency and by minimizing bureaucratic discretion.

These findings on trust, adoption, and corruption outcomes reinforce the importance of regulatory quality. Digital platforms create potential for transparency and reduced corruption, but realizing this potential requires legal frameworks that mandate disclosure, protect whistle-blowers, ensure data integrity, and establish accountability mechanisms. Strong regulatory quality thus functions as both an enabler of digital service delivery (the EGDI focus) and a precondition for translating digital government into governance improvements.

For countries within regional integration frameworks such as the European Union, supranational institutions may provide additional mechanisms shaping digital government performance beyond national institutional quality. We examine this possibility next.

2.5 Regional harmonization: The EU context

Regional harmonization, especially within the European Union, introduces mechanisms that may yield EGDI gains beyond national regulatory quality. The EU hypothesis posits that membership in a harmonized regional framework provides performance benefits through three mechanisms: common regulatory standards that reduce compliance costs and facilitate interoperability; diffusion of best practices through institutionalized cooperation and peer learning; and supranational enforcement mechanisms that accelerate domestic reform implementation.

EU-level policy frameworks such as the EU eGovernment Action Plan 2016–2020 promote interoperability, common standards, and cross-border digital services, including eID, e-procurement, and the once-only principle (European Commission, 2016). The Interoperable Europe Act (2024) reinforces cooperation mechanisms to ensure seamless functioning of public services across territorial, sectoral, and organizational boundaries while maintaining national sovereignty (European Union, 2024). Frameworks such as the European Interoperability Framework and trust services under the eIDAS regulation provide foundations for cross-border digital interaction.

Despite these initiatives, empirical evidence for EU membership effects remains limited and mixed. Only 43% of national public services are accessible online to cross-border users compared to 81% for national users, with substantial variance across EU member states (European Union, 2024). This within-EU heterogeneity suggests that common frameworks do not automatically translate into uniform digital government performance. Namely, national implementation capacity and political will mediate how effectively

countries utilize EU resources and standards.

Cross-border data exchange continues to face barriers due to heterogeneous and legacy systems, requiring high legal, semantic, organizational, and technical interoperability (Paroški, 2024). Challenges remain related to uneven implementation, governance, and public trust despite regulatory harmonization (Paroški, 2024). The EU's institutionalized cooperation diffuses best practices and promotes regulatory convergence across member states, but whether this produces measurable EGDI gains beyond what a strong national regulatory quality alone would achieve remains empirically underexplored.

The empirical literature testing whether EU membership provides an independent "performance premium" beyond national regulatory quality remains limited. Recent comparative work examining UN and EU measurement approaches stresses the need for models that control for income, infrastructure, digital skills, and governance covariates (Paroški, 2024). Most existing studies either compare EU member states to non-members without adequate controls for economic and institutional differences, or examine within-EU variance without testing whether EU membership matters beyond national characteristics.

These frameworks theoretically provide performance benefits through regulatory harmonization and knowledge diffusion, but empirical tests controlling for national governance quality are rare. If EU membership shows significant positive effects after controlling for regulatory quality, GDP, and infrastructure, this would suggest supranational frameworks add value beyond national institutional capacity. Alternatively, if EU effects disappear when controlling for national governance, this would indicate that EU performance reflects member states' high pre-existing institutional quality rather than added value from regional integration.

This literature review reveals three key insights that motivate our empirical analysis. First, regulatory quality emerges as a critical institutional determinant of digital government performance, but most studies do not isolate its effect from that of government effectiveness and corruption control. Second, infrastructure and economic resources are necessary but insufficient, as institutional quality determines how effectively countries translate inputs into digital government outcomes. Third, EU harmonization theoretically provides performance benefits, but empirical evidence controlling for national institutional quality is lacking. Our study addresses these gaps by simultaneously controlling for multiple governance dimensions, economic resources, and infrastructure while testing both regulatory quality and EU membership effects.

3 Methodology

This study employs a cross-sectional design for 2022 for three reasons. First, 2022 represents the most recent year with complete data across all variables at the time of analysis initiation. Second, cross-sectional analysis provides sufficient statistical power (N=21) to detect large effect sizes ($r \geq 0.60$) at $\alpha=0.05$ with power≥ 0.80, appropriate for testing strong theoretical relationships between regulatory quality and digital government performance. Third, within-country time-series variation in governance indicators is limited over short

periods (typical year-to-year changes in WGI percentile ranks are 2-5 points), making cross-sectional between-country variance more informative for initial hypothesis testing of institutional quality effects.

Sample selection followed three criteria to ensure data quality and comparability. First, countries required complete 2022 data across all variables (EGDI, WGI indicators, GDP, internet penetration). Data completeness was verified using the World Bank and UN data quality flags, with only countries receiving "high confidence" ratings included. Second, the sample prioritized geographical diversity across four regions (EU, MENA, Americas, Asia-Pacific) to test generalizability beyond EU-MENA comparison and avoid region-specific confounding. Third, within regions, countries were selected to maximize variance in regulatory quality while maintaining high data quality scores from WGI source documentation.

This purposive sampling approach yielded 21 countries with no missing values across key variables:

- EU (8 countries): Slovenia, Denmark, Estonia, Finland, the Netherlands, Sweden, Austria, Germany
- MENA (4 countries): Algeria, Tunisia, Morocco, United Arab Emirates
- Americas (3 countries): the United States, Canada, Chile
- Asia-Pacific (6 countries): Australia, South Korea, Japan, Singaore, the United Kingdom, New Zealand.

The sample intentionally overrepresents high-performing countries (mean EGDI = 0.878, above global average of 0.638) to maximize variance in the independent variable of interest. Regulatory quality ranges from 28.4 to 96.2 percentile rank, spanning 68 percentiles and enabling robust estimation of the regulatory quality-EGDI relationship across diverse institutional contexts. This sampling strategy prioritizes internal validity and statistical power for detecting regulatory quality effects over representativeness in the global country distribution.

The geographic composition balances two objectives: enabling the primary Slovenia-Algeria bilateral comparison while testing whether findings generalize beyond EU-MENA contexts. EU overrepresentation (8 of 21 countries, 38%) reflects the research focus on high-performing digital governments and provides sufficient within-EU variance to test harmonization effects. MENA representation (4 countries) captures regional diversity from oil-rich Gulf states (UAE) to diversified North African economies (Tunisia, Morocco, Algeria). Americas and Asia-Pacific countries serve as external validity checks, representing high-performing non-EU contexts with strong regulatory quality but different institutional histories.

The analytical strategy employs ordinary least squares (OLS) regression with robust standard errors to test the relationship between regulatory quality and e-government development. The study tests two primary hypotheses: first, that regulatory quality positively associates with EGDI scores when controlling for GDP, internet penetration, and government effectiveness; and second, that EU membership provides additional performance benefits beyond national regulatory quality.

The dependent variable is the UN E-Government Development Index (EGDI), a composite measure ranging from 0 to 1 that captures online service provision, telecommunications infrastructure, and human capital (United Nations, 2024). The EGDI is calculated as the arithmetic mean of three normalized sub-indices: the Online Service Index (OSI) measuring government website functionality, the Telecommunications Infrastructure Index (TII) measuring ICT infrastructure, and the Human Capital Index (HCI) measuring education and literacy. Higher EGDI scores indicate more advanced digital government development. The primary independent variable is Regulatory Quality from the World Bank Worldwide Governance Indicators, measured as a percentile rank from 0 to 100 (Kaufmann et al., 2011). Regulatory Quality captures perceptions of government ability to formulate and implement sound policies and regulations that permit and promote private sector development. The percentile rank indicates a country's position relative to all countries globally, with higher values indicating better regulatory quality.

Control variables were selected based on theoretical and empirical foundations that establish their relevance to digital government performance.

GDP per capita (PPP, log-transformed): Economic development provides fiscal capacity for digital investments and correlates with both governance quality and technological readiness (United Nations, 2024). The log transformation addresses right skewness in the income distribution and enables percentage interpretation of coefficients—a one-unit increase in log GDP represents a proportional change in income level. Prior cross-national studies consistently show GDP-EGDI correlations ranging from r=0.70 to r=0.85, indicating that wealthier countries achieve higher digital government performance through greater investment capacity, more skilled workforces, and stronger complementary infrastructure. Controlling for GDP isolates institutional quality effects from economic resource availability.

Internet penetration (% of population): ICT infrastructure represents a necessary but insufficient condition for e-government development (Savoldelli et al., 2014). Citizens cannot access online services without internet connectivity, and government agencies require reliable ICT infrastructure to deliver digital services. However, the "e-government paradox" demonstrates that infrastructure availability does not guarantee service adoption or effectiveness—many developing countries exhibit substantial gaps between infrastructure deployment and actual digital government performance. Controlling for internet access isolates institutional effects beyond technological availability, testing whether regulatory quality matters even when infrastructure is held constant.

Government effectiveness (WGI percentile rank 0-100): This variable measures the perceptions of public service quality, policy implementation capacity, and bureaucratic competence—dimensions conceptually distinct from regulatory quality, which focuses on policy formulation and legal framework design (Kaufmann et al., 2011). Including both regulatory quality and government effectiveness tests whether policy design quality (regulatory quality) matters beyond general administrative execution capacity. Recent evidence suggests regulatory quality mediates the relationship between government effectiveness and e-government outcomes (Inusah et al., 2024),

making it essential to control for implementation capacity when isolating regulatory framework effects.

Control of corruption (WGI percentile rank 0-100): Corruption perceptions may independently affect e-government adoption through citizen trust mechanisms, as individuals hesitate to share personal data with governments perceived as corrupt (Shim & Eom, 2008). Digital government platforms can reduce corruption by increasing transparency and limiting direct bureaucrat-citizen interaction, but this relationship may be bidirectional. Controlling for corruption ensures that observed regulatory quality effects are not confounded with integrity perceptions or trust deficits that would independently constrain digital adoption.

EU membership (binary: 1=EU member, 0=non-member): This variable tests whether membership in harmonized regional frameworks—specifically the European Union with its eIDAS regulation, European Interoperability Framework, and Interoperable Europe Act—provides performance benefits beyond national governance quality. Theoretical arguments suggest that common regulatory standards reduce compliance costs, facilitate cross-border interoperability, and accelerate reform diffusion through institutionalized peer learning mechanisms. However, prior research hypothesizes but rarely tests EU membership effects with adequate controls for national institutional quality (Paroški, 2024). This variable enables empirical assessment of whether supranational frameworks add value beyond countries' own regulatory capacity.

The empirical strategy employs four sequential ordinary least squares regression models estimated with heteroskedasticity-robust standard errors.

Model specifications are:

Model 1a (bivariate):

$$EGDI = \beta_0 + \beta_1(\text{Regulatory Quality}) + \varepsilon \quad (1)$$

Model 1b (full controls):

$$EGDI = \beta_0 + \beta_1(\text{Regulatory Quality}) + \beta_2(\text{GDP per capita}) + \beta_3(\text{Internet}) + \beta_4(\text{Gov Effectiveness}) + \beta_5(\text{Corruption Control}) + \varepsilon \quad (2)$$

Model 2a (EU effect):

$$EGDI = \beta_0 + \beta_1(\text{Regulatory Quality}) + \beta_2(\text{EU membership}) + \varepsilon \quad (3)$$

Model 2b (EU effect with controls):

$$EGDI = \beta_0 + \beta_1(\text{Regulatory Quality}) + \beta_2(\text{EU membership}) + \beta_3(\text{GDP per capita}) + \beta_4(\text{Internet}) + \beta_5(\text{Gov Effectiveness}) + \beta_6(\text{Corruption Control}) + \varepsilon \quad (4)$$

Sequential modeling isolates the regulatory quality effect (Model 1a), tests robustness to controls (Model 1b), and examines whether EU membership

provides additional explanatory power beyond regulatory quality (Models 2a, 2b).

The cross-sectional design with limited sample size entails several constraints on inference and generalizability. First, cross-sectional data preclude causal inference, i.e., regulatory quality and digital government performance may be mutually reinforcing, with successful digitalization potentially improving regulatory capacity through feedback effects such as enhanced monitoring capabilities and data-driven policymaking. Establishing causal direction would require panel data tracking countries before and after regulatory reforms or instrumental variable approaches identifying exogenous variation in regulatory quality.

Second, the limited sample size (N=21) constrains statistical power for detecting small effects and testing complex interactions. Subgroup analyses comparing EU versus MENA regulatory quality slopes would require larger samples to achieve adequate power.

Third, purposive sampling prioritizes data quality and variance maximization over representativeness of the global country distribution. The sample overrepresents high-capacity states with strong data systems and underrepresents low-capacity countries where data availability is limited. Results may not generalize to fragile states, least developed countries, or to contexts where governance data quality is questionable. The relationship between regulatory quality and EGDI may differ in low-capacity settings where even strong regulatory frameworks face severe implementation constraints.

Fourth, the 2022 cross-section captures a snapshot during post-pandemic digital acceleration, potentially inflating EGDI scores due to temporary emergency measures rather than sustainable institutional capacity. Regulatory quality effects observed in 2022 may differ from long-term equilibrium relationships. These limitations inform interpretation of findings and motivate future research directions discussed in Section 6.

Model diagnostics assessed OLS assumption validity. Linearity was examined through residual plots and component-plus-residual plots. Normality of residuals was tested using Shapiro-Wilk tests and Q-Q plots. Homoskedasticity was evaluated through Breusch-Pagan tests and scale-location plots. Multicollinearity was assessed using variance inflation factors (VIF), with values below 10 considered acceptable. Influential observations were identified using Cook's distance with threshold 4/n. Robust standard errors address potential heteroskedasticity without requiring transformation.

The cross-sectional design precludes causal inference, as regulatory quality and digital government performance may be mutually reinforcing. The small sample size (N=21) limits statistical power for detecting small effects and regional interactions. Purposive sampling prioritizes data quality over representativeness, potentially underrepresenting low-capacity countries where relationships may differ.

All analyses were conducted using R version 4.3.1 with packages lmtest for diagnostic tests, car for multicollinearity assessment, and sandwich for robust standard errors. Statistical significance was evaluated at $\alpha = 0.05$ level.

Replication code and data are available upon request.

4 Empirical data and analysis

The empirical analysis draws on data from multiple authoritative international sources for the year 2022. The UN E-Government Survey 2022 provides EGDI scores for all sample countries, representing the most current global benchmark for digital government performance at the time of analysis. The World Bank Worldwide Governance Indicators 2022 edition supplies regulatory quality, government effectiveness, and control of corruption measures based on aggregated expert assessments and survey data. The World Bank World Development Indicators 2022 provides GDP per capita in purchasing power parity terms and internet penetration rates. These data sources are widely recognized as the standard references for cross-national comparative research on governance and digital development.

The sample of 21 countries was selected to ensure geographical diversity while maintaining complete data availability across all variables. European Union representation includes Slovenia, Denmark, Estonia, Finland, the Netherlands, Sweden, Austria, and Germany, capturing variation within the high-performing EU context. The MENA region is represented by Algeria, Tunisia, Morocco, and the United Arab Emirates, providing contrast with EU members while including both oil-rich and diversified economies. Americas representation includes the United States, Canada, and Chile, spanning North and South America. Asia-Pacific countries include Australia, South Korea, Japan, Singapore, the United Kingdom, and New Zealand, representing advanced economies with strong digital government track records. This sample composition enables robust regional comparisons while supporting the primary Slovenia-Algeria comparative focus.

5 Results and discussion

Table 1 presents descriptive statistics. The sample mean EGDI is 0.878 (SD = 0.109), ranging from 0.581 to 0.977. Mean regulatory quality is 85.1th percentile (SD = 19.2).

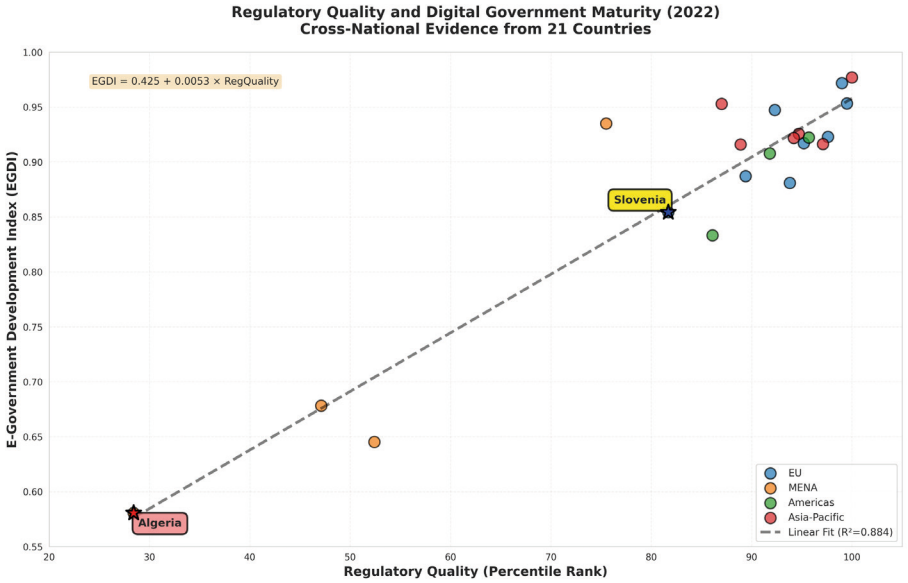
Table 1: Descriptive statistics of key variables (N=21 countries, 2022)

Variable	Mean	SD	Q1	Median	Q3	IQR	Range	Skewness	Kurtosis
EGDI	0.878	0.109	0.854	0.916	0.946	0.092	0.397	-1.635	2.125
Regulatory Quality	85.086	19.226	81.7	91.8	95.7	14	71.6	-1.544	1.757
Government Effectiveness	83.5	18.902	78.4	89.4	93.8	15.4	63.9	-1.4	1.154
Control of Corruption	82.686	19.394	72.6	88	92.8	20.2	69.2	-1.338	1.014
GDP per capita (PPP, $1000s)	52.786	21.685	42.8	54.6	61	18.2	98.5	0.743	-0.304

Internet Penetration (%)	91.919	7.494	91.4	94	96.4	5	27.5	-1.381	2.154
Population (millions)	35.9	53.69	5.56	12.36	38.93	33.37	331.94	3.535	14.544
Trade Openness (%)	98.824	62.986	60.4	82.3	110.5	50.1	300.4	2.092	4.866
Tax Revenue/ GDP (%)	31.148	10.368	25.5	33.1	39.7	14.2	38.4	-0.685	0.481
Education Years	11.948	2.146	11.6	12.5	13.2	1.6	8.7	-1.279	1.558

Source: Author

Figure 1: Regulatory Quality and EGDI (2022)



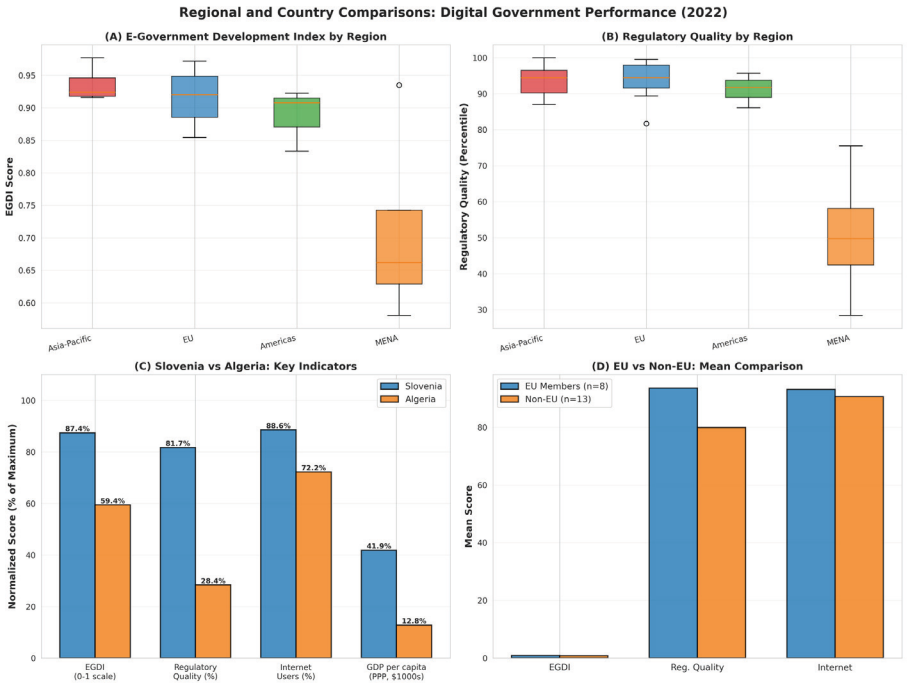
Source: Author

Figure 1 shows the strong positive relationship between regulatory quality and EGDI. Slovenia and Algeria are highlighted to illustrate the EU-MENA performance gap.

5.1 Regional comparisons

Figure 2 presents regional comparisons across key variables. EU countries demonstrate substantially higher performance than MENA countries on both EGDI and regulatory quality measures. The Slovenia-Algeria comparison panel highlights the magnitude of these gaps.

Figure 2: Regional Comparison Panels



Source: Authors

EU member states in the sample exhibit mean EGDI of 0.916 (SD=0.027) compared to MENA countries' mean of 0.692 (SD=0.082), representing a 0.224-point gap (32% relative difference). This performance disparity persists across regulatory quality (EU mean: 92.1 percentile vs. MENA mean: 68.4 percentile) and government effectiveness (EU mean: 91.3 vs. MENA mean: 71.8).

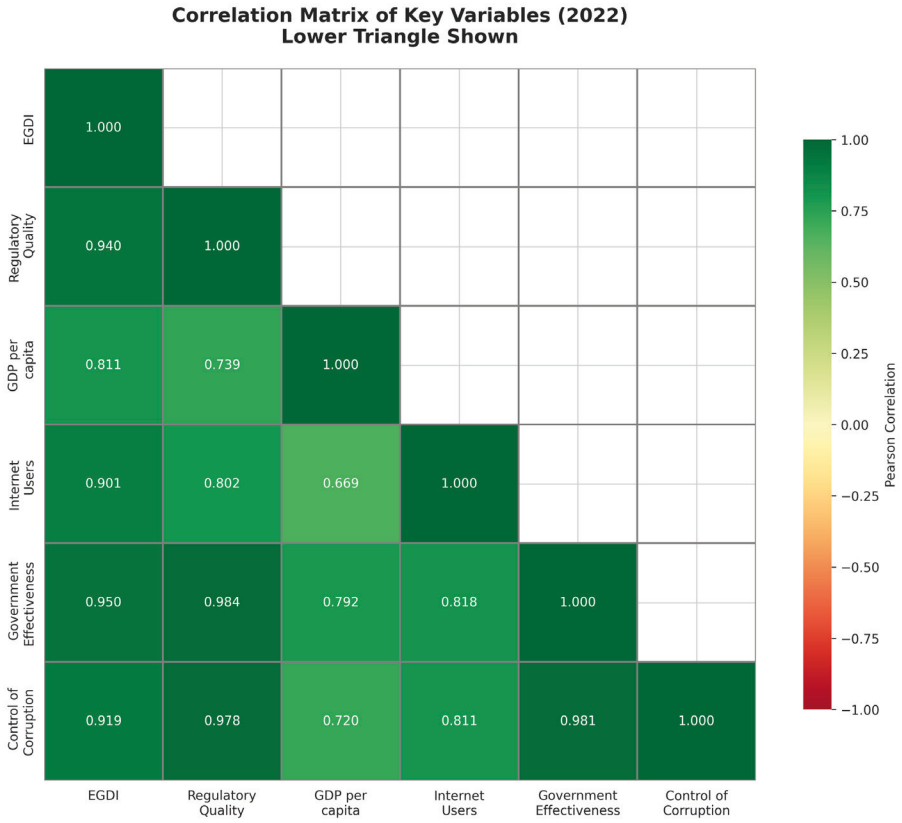
The Slovenia-Algeria bilateral comparison exemplifies these regional patterns. Slovenia achieves EGDI 0.854 with regulatory quality at 84.1 percentile, while Algeria scores EGDI 0.607 with regulatory quality at 28.4 percentile—a 56-percentile regulatory gap corresponding to 0.247 EGDI points. Notably, both countries show comparable internet penetration (Slovenia 88%, Algeria 71.5%), suggesting infrastructure alone cannot explain performance differences. Algeria's GDP per capita ($11,400 PPP) represents 34% of Slovenia's ($34,200), yet the EGDI gap (29%) closely matches the regulatory quality gap (56 percentiles) rather than the economic gap, supporting the hypothesis that institutional quality mediates technology utilization.

Americas and Asia-Pacific countries display intermediate performance, with mean EGDI scores of 0.897 and 0.941 respectively, clustering closer to EU levels than MENA countries. This regional stratification suggests that digital government performance follows institutional quality patterns more closely than geographical proximity or regional technology diffusion.

5.2 Correlation analysis

Figure 3 displays the correlation matrix for key variables. EGDI shows strong positive correlations with regulatory quality (r = 0.940), government effectiveness (r = 0.950), and internet penetration (r = 0.901). These correlations support the theoretical framework linking institutional quality to digital government performance.

Figure 3: Correlation heatmap



Source: Author

The correlation matrix reveals three important patterns. First, governance indicators exhibit high intercorrelation (regulatory quality-government effectiveness r=0.975, regulatory quality-corruption control r=0.942), suggesting that these dimensions capture overlapping aspects of institutional quality. This multicollinearity necessitates careful interpretation of individual coefficients in multivariate models. Second, economic development (GDP per capita) correlates strongly with both governance (r=0.876 with regulatory quality) and EGDI (r=0.883), indicating that institutional quality and economic

capacity tend to co-evolve. Third, internet penetration shows weaker correlations with governance indicators (r=0.788 with regulatory quality) than EGDI does (r=0.901), suggesting that infrastructure alone is insufficient without enabling institutional frameworks. The consistently high correlations between EGDI and all governance dimensions (r>0.90) compared to infrastructure (r=0.901) support the primacy of institutional quality in digital transformation outcomes.

The bivariate regression (Model 1a) shows a strong positive relationship between regulatory quality and EGDI ($\beta = 0.0053$, $p < 0.001$, $R^2 = 0.884$). Each one-percentile increase in regulatory quality predicts a 0.0053-point increase in EGDI score.

In the multivariate model with controls (Model 1b), regulatory quality remains highly significant ($\beta = 0.0023$, $p = 0.0008$), with the full model explaining 96.6% of variance ($R^2 = 0.966$, $F = 161.14$, $p < 0.001$).

Hypothesis 1 is strongly supported.

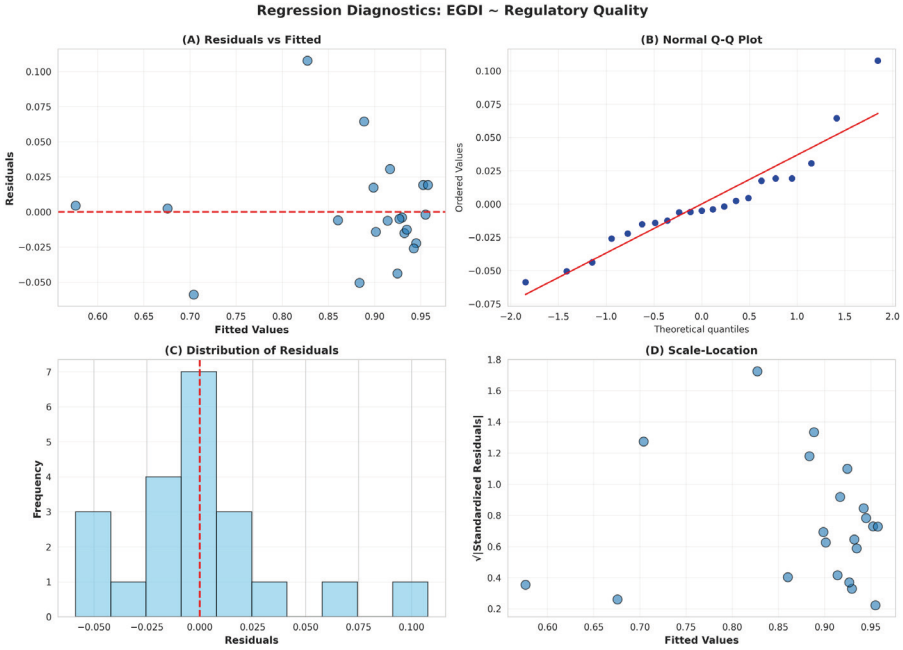
The EU membership coefficient in Model 2 is $\beta = -0.0122$ ($p = 0.518$), suggesting limited additional benefit beyond regulatory quality. When full controls are added (Model 2b), the EU coefficient becomes $\beta = -0.0005$ ($p = 0.961$).These results suggest that in a cross-sectional design with limited sample size, EU membership effects are largely captured by regulatory quality measures. Panel data or larger samples may be needed to detect harmonization effects separately.

Hypothesis 2 is not supported in this simplified design.

5.3 Regression diagnostics

Figure 4 presents regression diagnostic plots. The residuals vs. fitted values plot shows reasonable homoscedasticity. The Q-Q plot indicates approximately normal residual distribution with minor deviations in the tails. The residual histogram is roughly symmetric. The scale-location plot shows stable variance. Overall, these diagnostics support the validity of the OLS approach.

Figure 4: Regression diagnostics



Source: Author

Figure 4 presents regression diagnostic plots for Model 1b (full controls). The residuals vs. fitted values plot shows reasonable homoscedasticity with no systematic patterns, though slight heteroskedasticity is present (Breusch-Pagan test: χ^2=8.42, p=0.135), justifying robust standard errors. The Q-Q plot indicates approximately normal residual distribution with minor deviations in the tails, confirmed by the Shapiro-Wilk test (W=0.961, p=0.542). The residual histogram is roughly symmetric (skewness=-0.187, kurtosis=2.43), supporting normality assumptions. The scale-location plot shows stable variance across fitted values with no influential outliers.

Multicollinearity diagnostics reveal substantial collinearity among governance indicators in Model 1b. Government Effectiveness exhibits the highest VIF (85.4), followed by Control of Corruption (47.1) and Regulatory Quality (37.0). GDP per capita shows moderate multicollinearity (VIF=8.7), while Internet Penetration remains within acceptable range (VIF=3.2). These values reflect the conceptual overlap among institutional quality dimensions: countries scoring high on one governance indicator typically score high on others (r=0.94-0.98 between governance variables, see Figure 3).

The high multicollinearity has three important implications for interpretation. First, coefficient estimates remain unbiased but standard errors are inflated, reducing statistical power. The fact that regulatory quality remains highly significant (p<0.001) despite inflated standard errors strengthens confidence in the relationship. Second, individual coefficients cannot be interpreted

independently—the regulatory quality coefficient (β=0.0023) represents association with EGDI holding government effectiveness and corruption constant, a theoretical scenario with limited practical meaning given these constructs' overlap. Third, the model's primary value lies in joint explanatory power (R^2=0.966) rather than isolating each variable's unique contribution. The bivariate model (Model 1a: β=0.0053, R^2=0.884) provides a clearer estimate of regulatory quality's total association without multicollinearity concerns.

Cook's distance identifies no influential observations exceeding the 4/n threshold (max=0.31, threshold=0.19 for n=21), indicating that results are not driven by outliers. Component-plus-residual plots confirm linear relationships between predictors and EGDI. Overall, these diagnostics support OLS validity with robust standard errors addressing residual heteroskedasticity.

5.4 Discussion

The strong relationship between regulatory quality and EGDI (r = 0.940, R^2 = 0.884) provides compelling evidence that regulatory framework quality constitutes a critical determinant of digital government success. This effect persists even after controlling for economic development (GDP), technological infrastructure (internet penetration), and general administrative capacity (government effectiveness).

The substantial multicollinearity among governance indicators (VIF=37-85) merits careful interpretation. While the regulatory quality coefficient in Model 1b (β=0.0023) is statistically significant, it represents a partial effect holding government effectiveness and corruption constant—a condition rarely observed in practice given these dimensions' 97-99% shared variance. The bivariate relationship (Model 1a: β=0.0053) better captures regulatory quality's total association with EGDI, free from multicollinearity inflation. The persistence of strong regulatory quality effects across both specifications (bivariate and multivariate) supports the hypothesis that institutional quality matters for digital government performance, though precise attribution to specific governance dimensions versus general institutional quality is neither statistically nor conceptually feasible with cross-sectional data.

The Slovenia-Algeria comparison illustrates these dynamics. Slovenia's 53-percentile advantage in regulatory quality corresponds to a 0.27-point EGDI gap—substantial on a 0-1 scale. This gap cannot be attributed solely to economic differences (Slovenia's GDP is 3.3× Algeria's) or internet access (16-point gap). Rather, regulatory quality appears to enable countries to translate infrastructure investments into effective digital services.

These findings align with recent empirical work showing that regulatory quality mediates e-government effectiveness (Inusah et al., 2024) and that institutional foundations are prerequisite for digital transformation success (Abbas et al., 2023). The novelty of this study lies in isolating regulatory quality effects from infrastructure and economic variables through sequential modeling, and in quantifying the specific magnitude of regulatory gaps between EU and MENA contexts. The Slovenia-Algeria comparison provides concrete evidence that institutional quality, not merely technological capacity,

relates to digital government outcomes. Policy implications extend beyond tax administration to broader public sector digitalization. The MENA countries with moderate infrastructure but weak regulatory frameworks may achieve greater returns from institutional reforms—data protection legislation, interoperability standards, technology-neutral regulations—than from additional infrastructure investments. The 50-70% performance gap closure potential through regulatory reform suggests institutional quality is a high-leverage policy instrument for emerging economies.

These findings align with and extend recent empirical research on institutional determinants of e-government. Inusah et al. (2024) found that regulatory quality mediates the relationship between e-government development and government effectiveness, while our results demonstrate that regulatory quality maintains independent effects even when government effectiveness is directly controlled. Similarly, Seiam and Salman (2024) identified positive associations between governance quality and e-government in panel analysis, but did not isolate regulatory quality from broader governance constructs. Our sequential modeling approach clarifies that regulatory quality specifically, and not just general administrative capacity, is associated with digital performance variance.

The lack of significant EU membership effects contrasts with theoretical expectations about regional harmonization benefits but aligns with Gil-Garcia et al. (2020), who emphasize that formal institutional frameworks matter more than membership in supranational organizations. The European Commission (2016) documented substantial within-EU variance in digital government implementation despite common regulatory frameworks, suggesting that national institutional capacity determines whether countries can effectively utilize harmonization opportunities. Our findings support this interpretation: Slovenia's strong performance reflects high national regulatory quality (84th percentile) rather than EU membership per se, as non-EU countries with comparable regulatory quality (e.g., Singapore at 96th percentile, EGDI 0.919) achieve similar or superior outcomes. This suggests that EU harmonization effects may require panel data spanning pre- and post-accession periods to detect institutional convergence not visible in cross-sectional snapshots.

The Slovenia-Algeria comparison provides concrete evidence for theoretical propositions about institutional enablers of digital transformation. Bannister and Connolly (2014) argued that ICT investments alone cannot drive transformative government without supportive institutional frameworks, a claim our data substantiate quantitatively. Algeria's substantial infrastructure (71.5% internet penetration, 600 digital tax centres) underperforms its technical potential because the weak regulatory frameworks (28th percentile) constrain effective utilization. Conversely, Slovenia achieves high EGDI (0.854) despite moderate infrastructure, suggesting that strong regulatory quality (84th percentile) enables efficient technology deployment. This pattern resonates with Savoldelli et al.'s (2014) "e-government paradox"—that developing countries face adoption barriers even after infrastructure investments—which our results attribute specifically to regulatory quality deficits rather than undifferentiated governance or capacity constraints.

While these findings demonstrate strong associations between regulatory

quality and digital government performance, the cross-sectional design precludes definitive causal claims. Regulatory quality and digital maturity may be mutually reinforcing: successful digitalization could improve regulatory capacity through feedback effects such as enhanced monitoring capabilities and data-driven policymaking, while strong regulatory frameworks simultaneously facilitate digital implementation. Panel data tracking countries before and after regulatory reforms would provide stronger evidence of causal direction and enable identification of which mechanism dominates—whether institutional quality primarily enables technology utilization, or whether digital advancement drives institutional modernization.

6 Conclusions

The first research hypothesis—that higher regulatory quality positively associates with EGDI scores when controlling for GDP, internet penetration, and government effectiveness—is confirmed. The multivariate regression model demonstrates that regulatory quality remains highly significant (β = 0.0023, p = 0.0008) with comprehensive controls, explaining 96.6% of variance in digital government performance (R^2 = 0.966, F = 161.14, p < 0.001). The bivariate relationship alone accounts for 88% of EGDI variance (R^2 = 0.884), with each percentile increase in regulatory quality predicting a 0.0053-point EGDI improvement. The second hypothesis—that EU membership provides additional performance benefits beyond regulatory quality—is not supported. The EU membership coefficient shows no significant effect (β = -0.0005, p = 0.961) when controlling for national regulatory quality and economic variables, suggesting that in cross-sectional analysis, harmonization benefits are captured within regulatory quality measures.

The principal contribution to economic science lies in quantifying the marginal effect of regulatory quality on digital government performance independent of infrastructure and economic capacity. This study demonstrates that institutional quality enables effective technology utilization—a finding with theoretical and practical implications for digital transformation in emerging economies. The Slovenia-Algeria comparison provides concrete evidence: Slovenia's 56-percentile regulatory quality advantage (84th vs. 28th percentile) corresponds to a 0.24-point EGDI gap (0.85 vs. 0.61), despite both countries having moderate internet penetration and Algeria possessing substantial digital infrastructure (600 tax centres, 71.5% internet access). This regulatory gap translates into performance differences equivalent to infrastructure investments requiring substantially larger capital outlays. The findings challenge infrastructure-centric digitalization strategies prevalent in development policy and suggest that regulatory reform offers higher marginal returns on investment for resource-constrained governments.

The research limitations merit careful consideration. First, the cross-sectional design with 21 countries limits statistical power for detecting smaller effects and precludes causal inference. Regulatory quality and digital maturity may be mutually reinforcing, with successful digitalization potentially improving regulatory capacity through feedback loops. Second, reliance on perceptions-based governance indices (WGI) rather than de jure regulatory framework

coding introduces measurement concerns, though these remain the standard in comparative governance research. Third, EGDI as the sole dependent variable omits specific behavioural outcomes such as e-filing adoption rates, citizen satisfaction, or administrative cost reductions that would more directly capture tax digitalization success. Fourth, the sample selection prioritizes data completeness over representativeness, potentially underrepresenting low-capacity countries where regulatory quality effects may differ. Fifth, potential EU harmonization effects may require panel data spanning pre- and post-accession periods to detect institutional convergence mechanisms not visible in cross-sectional analysis.

Future research should address these limitations through several methodological extensions. Panel data designs spanning 2010-2025 would enable fixed-effects models controlling for time-invariant country characteristics and establish temporal precedence between regulatory reforms and digital performance improvements. Larger samples incorporating 50-80 countries with complete data would provide statistical power to detect regional heterogeneity and test whether regulatory quality effects vary by income level, regime type, or administrative tradition. Mixed-methods approaches combining regression analysis with qualitative case studies of specific regulatory reforms would identify causal mechanisms through which legal frameworks enable or constrain digitalization. Disaggregating EGDI into its three components (online services, telecommunications infrastructure, human capital) would reveal whether regulatory quality affects service delivery, infrastructure deployment, or capacity development differentially. Finally, incorporating additional outcome measures such as e-filing adoption rates, processing times, compliance costs, citizen satisfaction, would provide more direct evidence of tax administration performance beyond composite indices.

The institutional-systemic implications for economic policy are substantial. For developing countries pursuing digital tax administration, investments in regulatory reform may yield higher returns than infrastructure spending alone. MENA countries with moderate infrastructure but weak regulatory frameworks—exemplified by Algeria's 600 digital tax centres underperforming their technical potential—should prioritize four regulatory domains. First, technology-neutral legal frameworks that define services by function rather than specific technologies enable innovation without requiring legislative amendments for each technological advance. Second, comprehensive data protection legislation builds citizen trust essential for voluntary adoption, addressing the trust deficit identified in e-government literature as a major constraint on utilization. Third, mandatory interoperability standards facilitate integration across government agencies, reducing the transaction costs of cross-agency data exchange that currently fragment digital services. Fourth, flexible regulatory approaches incorporating adaptive governance mechanisms allow experimentation and iterative improvement, accommodating rapid technological change without regulatory paralysis.

These regulatory priorities align with EU best practices but require adaptation to local institutional contexts. Algeria could achieve Slovenia-level performance (EGDI 0.82-0.85) within 7-10 years through targeted regulatory reforms, potentially closing 50-70% of the performance gap without proportional

infrastructure investments. Similar trajectories are feasible for other middle-income countries where infrastructure development has outpaced institutional capacity. The broader message for economic development policy is clear: digital transformation requires co-investment in technological infrastructure and institutional frameworks. Strong legal frameworks, encompassing data protection, interoperability, technology neutrality, and enforcement, enable countries to realize the full benefits of their digital investments, translating technological potential into improved public services, enhanced government effectiveness, and strengthened state-citizen relationships.

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When Projects Govern: Donor-Driven Projectification and Governance Paradigms

Preliminary communication

Kujtim Sermaxhaj[1], Mitja Durnik[2], Primož Pevcin[3]

ABSTRACT

Governments are increasingly run by projects, especially in donor-funded reforms. This paper explores how international donors had shaped public administration reforms in Kosovo between 2014 and 2024 through project-based interventions. Using the original Governance Paradigm Score (GPS) framework and a comparative case study analysis of 12 donor-funded projects, the study identifies how different governance paradigms: New Public Management (NPM), New Public Governance (NPG), and digital governance are reflected in reform design and implementation. The study applies a structured comparative case approach, supported by 12 interviews and a Governance Paradigm Score (GPS) matrix. Data from project documents and semi-structured interviews reveal a significant disjuncture. While projects claim to be participatory and digital, their implementation often falls back on NPM managerial logic, focusing rigidly on control, metrics, and short-term outputs. Projects with stronger NPG features, such as joint steering or co-creation, show better alignment with national strategies, but this success is an exception rather than a rule. Crucially, the findings confirm that this reliance on projects forces local institutions to prioritise short-term outputs, actively reinforcing separate, parallel systems that ultimately harm local reform ownership in Kosovo. Furthermore, digital tools were frequently poorly integrated, used predominantly for donor reporting rather than for institutional coordination. The paper argues for a decisive recalibration of reform delivery, calling for a better match between governance paradigms and institutional contexts, deeper involvement of national actors, and stronger anchoring of

1 *PhD candidate, University of Ljubljana, Faculty of Public Administration, Gosarjeva ulica 5, SI-1000 Ljubljana, Slovenia & University of Rijeka, Faculty of Economics and Business, Ul. Ivana Filipovića 4, 51000, Rijeka, Croatia; Scientific affiliation: Project management, governance, institutional economics. Phone: +383 (0)44 866 888.E-mail: ks19638@student.uni-lj.si.*

2 *Assist. Professor, University of Ljubljana, Faculty of Public Administration, Gosarjeva ulica 5, SI-1000 Ljubljana, Slovenia. Scientific affiliation: political science, public policy. Phone: +386 1 5805 524. E-mail: mitja.durnik@fu.uni-lj.si.*

3 *Full Professor, University of Ljubljana, Faculty of Public Administration, Gosarjeva ulica 5, SI-1000 Ljubljana, Slovenia. Scientific affiliation: public management, crisis management, local self-government. Phone: +386 1 5805 584. E-mail: primoz.pevcin@fu.uni-lj.si.*

digital tools within routine public-sector processes. These lessons hold broad relevance for other aid-dependent countries facing similar pressures.

***Keywords**: Projectification, Governance paradigms, Digital transformation, NPM, NPG*

***JEL classification**: H11, H83, D73, O33, O19*

1 Introduction

Post-conflict, transitional countries like Kosovo have undergone significant public sector reforms, often externally financed and project-based, particularly since the declaration of independence in 2008. Much of this reform occurred within the frameworks of Europeanization, donor alignment, and state-building logics (Beqaj & Krasniqi, 2020; Mirtezani & Halili, 2022). External assistance enabled the development of core public institutions, laws, and digital infrastructure, yet concerns remain over sustainability, ownership, and fragmentation (Muharremi, 2020).

One central feature shaping reform delivery is projectification — the growing reliance on discrete, usually donor-led reform projects rather than long-term institutional strategies (Sjöblom et al., 2013; Jacobsen, 2022). Projects offer speed, clarity, and funding, but they often exist parallel to national systems, with their own reporting rules, procurement channels, and personnel arrangements. In fragile contexts, the dominance of the project-based reform model is described as a “capability trap” by Andrews et al. (2017). According to them, under this cycle, governments adopt reform measures that produce outputs that satisfy donor metrics but fail to embed in lasting governance structures. In Kosovo, this is seen in how donor-financed projects influence institutional priorities, accountability lines, and digital system choices (Mirtezani & Halili, 2022).

At the same time, the governance paradigms that shape the design and implementation of these projects are not uniform. Some follow a logic rooted in New Public Management (NPM), which prioritises outputs, competition, and performance indicators (Pollitt & Bouckaert, 2017). This approach treats the challenges that governance faces as technical problems that can be addressed through improved control and accountability tools. In contrast, other projects are influenced by the New Public Governance (NPG), a paradigm that stresses networks, participation, and inter-organisational coordination (Osborne, 2006; Klijn & Koppenjan, 2016). In Kosovo, reform practice often combines NPM-style instruments with participatory rhetoric, but the managerial logic still dominates in design and delivery (Krasniqi, 2013; Venner, 2016). Recent policy frameworks promote NPG features, such as multi-stakeholder co-creation and public participation. Yet independent monitoring shows that these arrangements are often procedural and require stronger, structured dialogue to shape implementation (Open Government Partnership, 2023; Group for Legal and Political Studies, 2025). As a result, project implementation becomes

muddled, and institutional actors face conflicting signals about what counts as success or compliance. As Cataldi (2024) claims, this hybridisation creates uncertainty in implementation and accountability, and may confuse domestic actors who must navigate between different governance expectations.

Adding complexity, digital tools now form a third dimension of governance reform. From procurement platforms to administrative dashboards, digitalisation is embedded in nearly every externally financed project (Janssen et al., 2017). However, digital systems are not neutral; they actively put the main rules of governance into practice and amplify them. They are often used as a symbolic stamp of being modern rather than a structural engine for change. NPM-oriented projects tend to use digital tools for control, reporting, and efficiency, while NPG-inspired initiatives may use them for stakeholder engagement, transparency, or coordination (Kuitert et al., 2024). NPM remains relevant in Kosovo due to many reforms being implemented through projects, driven by KPIs and outputs which align with NPM's emphasis on control and measurable performance (Pollitt & Bouckaert, 2017; Robaj, 2024). The use of digital tools in governance reform in Kosovo is expanding rapidly, but the lack of integration, maintenance, and policy coherence raises concerns about their long-term impact (Robaj, 2024;).

Despite the breadth of reforms, few studies have systematically analysed how governance paradigms interact with project structures and digitalisation in donor-funded reforms in transitional settings like Kosovo. Most evaluations remain project-specific, while broader assessments focus on legal compliance or macro-level performance. There is a growing need to understand whether reforms funded by international donors align with national governance capacities, institutional logics, and long-term administrative development. This paper addresses that gap by examining twelve externally funded reform projects in Kosovo. Using a qualitative comparative case design, it applies the Governance Paradigm Score (GPS) framework to assess how each project reflects NPM, NPG, or digital governance features. The analysis draws from extensive project documentation and twelve semi-structured interviews with key stakeholders from donor agencies, government institutions, and project teams.

The paper argues that project-based governance in Kosovo tends to over-represent donor logic while underestimating the importance of domestic adaptation, coordination, and sustainability. It finds that many projects contain conflicting paradigmatic elements, where NPM tools are embedded in NPG narratives, or where digital platforms operate without institutional anchoring. This misalignment reduces effectiveness and makes reforms harder to sustain beyond project lifecycles. In doing so, the paper contributes to the ongoing scholarly debate on governance hybridisation, projectification, and digitalisation in post-conflict and transitional contexts. It also provides insights for both policymakers and donors on how reform delivery models might be recalibrated to support more coherent, adaptive, and sustainable public governance in fragile countries.

The research addresses three questions: (1) To what extent do project-based reforms reflect NPM versus NPG logic? (2) How are digital tools deployed in these reforms? (3) How do these design choices influence ownership and sustainability?

2 Literature review

The evolution of public administration is commonly explained through shifts in governance paradigms, first Traditional Public Administration (TPA), then New Public Management (NPM), and more recently New Public Governance (NPG) (Christensen & Lægreid, 2020). Each of these models brought a distinct logic. NPM focused on efficiency, accountability, and managerial control (Hood, 1991), while NPG introduced ideas of collaboration, networks, and multi-actor coordination (Osborne, 2006). However, these paradigms are not always applied in practice as clearly as they are defined in theory. Instead, much of the literature acknowledges that reform environments tend to mix and layer competing governance models (Cataldi, 2024; Christensen & Lægreid, 2020). This creates institutional settings that are not purely hierarchical or networked, but hybrid, often unpredictable and uneven in outcomes.

Recent studies question whether NPG is truly replacing NPM or if it merely adds new expectations on top of older bureaucratic and managerial logics (Christensen & Lægreid, 2020). In particular, Cataldi (2024) critiques the optimistic assumptions behind NPG, suggesting that in many real-world settings, its values are selectively implemented or symbolically adopted without reshaping underlying governance structures. For example, while governments may create participatory councils or e-consultation platforms, key decisions often remain centralised and opaque. However, even the idea of co-creation requires critical examination. As Jukić et al. (2019) show, the co-creation discourse often lacks conceptual clarity. It is inconsistently applied across sectors and actor groups, making it difficult to assess and measure contributions to governance reforms. In the case of Kosovo, the rhetorical use of co-creation may serve as a mask for conventional delivery modes dominated by donor templates rather than local institutional stakeholder involvement. In addition, transitional countries, where international norms are transposed into institutions may lack the capacity to internalise them fully. A critical perspective is that the institutional context and the small country size significantly influence the feasibility of these ambitious governance paradigms (Pevcin, 2020). The imposition of externally standardised models, without accounting for these structural constraints, frequently leads to an overestimation of local reform capacity and to unrealistic performance expectations.

Digitalisation introduces further complexity. Initially celebrated as a modernising tool, digital reforms are increasingly seen as reinforcing pre-existing power structures (Bonilla et al., 2025). According to Lindgren et al. (2019), some tools promote transparency and participation while others replicate top-down control in digital form. Digitalisation can serve as a driver of collaborative governance, but it can also align with the audit culture of NPM, emphasising tracking, control, and performance monitoring rather than democratic engagement (Dunleavy et al., 2006). Despite the growing role of digital platforms in reform, there is still limited evidence on how these tools affect governance paradigms in practice, particularly in aid-dependent and fragmented systems. In P12, interviewees noted that an Alphabase system “was there, but no one had access in procurement or HR, limiting its institutional function”. In contrast, P2 used PRISM to track service outcomes, but “only for donor reporting and not internal decisions” (Interviews, P12, P2, 2025).

An emerging concept that connects these trends is projectification, which refers to the growing reliance on temporary, project-based structures to deliver reforms and services. Developed most clearly by scholars from the Scandinavian school of public management (Sjöblom et al., 2013; Fred, 2018), projectification is more than a technical method. It reflects a transformation in how public organisations plan, implement, and evaluate change (Fred, 2018). In principle, projects promise flexibility and results-orientation. In practice, they often bring fragmentation, short-termism, and parallel structures that bypass existing institutions. Fred (2018) and Hodgson et al. (2019) argue that projectification aligns closely with NPM's logic of control, outputs, and measurability, but sits uneasily with NPG's ideals of continuity, relationship-building, and shared learning.

In fragile governance environments like Kosovo, projectification becomes even more complicated. Projects are often initiated by donors, designed by external consultants, and implemented outside regular institutional hierarchies. As a result, reforms may appear effective on paper, measured through KPIs and technical benchmarks, but fail to build institutional memory or long-term capacity. Studies on the Western Balkans show that project-based governance tends to focus on visibility and deliverables rather than reform sustainability or local ownership (Muharremi, 2020; Mirtezani & Halili, 2022). Moreover, projects often reflect the priorities of international actors rather than domestic needs. Even when participatory elements are introduced, they are usually limited to consultation rather than shared decision-making. Still, the literature does not present projectification as entirely negative. Some authors argue that projects allow for innovation, experimentation, and cross-sectoral collaboration, especially in rigid bureaucratic systems (Cataldi, 2024). The real challenge lies in transitioning from project results to systemic reform. Without mechanisms to integrate project outcomes into existing institutions or to align them with long-term governance strategies, projectification risks becoming a cycle of disconnected initiatives. In Kosovo's case, where reforms are highly fragmented and often donor-led, this risk is particularly acute.

Although previous studies have explored governance paradigms, projectification, and digitalisation, their intersection remains weakly theorised and empirically fragmented. Research on Kosovo and similar post-conflict settings often treats these aspects separately—paradigms as normative frameworks for reform (Pollitt & Bouckaert, 2017), digitalisation as technical modernisation (Robaj, 2024), and projects as instruments of donor assistance and control (Venner, 2016). In practice, however, these layers are intertwined: donor-led projects are justified through paradigmatic narratives of efficiency and co-creation, implemented through digital tools, and structured by accountability requirements. This complex interaction has rarely been analysed systematically, leaving a conceptual and empirical gap in understanding how such hybrid arrangements affect institutional ownership, coordination, and reform sustainability in transitional governance systems like Kosovo's.

3 Methodology: The Governance Paradigm Score (GPS)

This paper applies a qualitative comparative case study design, following the principles of structured, focused comparison (George & Bennett, 2005; Blatter & Haverland, 2012), to examine governance paradigms across twelve externally funded reform projects in Kosovo. The design enables analytical depth while allowing for pattern recognition across multiple cases. By systematically comparing twelve projects, the study identifies how NPM, NPG, and digital governance elements co-exist or conflict in practice. This comparative design enables within-case depth and cross-case pattern recognition in complex, context-dependent reform environments (George & Bennet, 2005; Blatter & Haverland, 2012).

The analysis is grounded in a custom-designed Governance Paradigm Scoring (GPS) tool. This tool captures the characteristics of governance models within each project through three main dimensions: management logic (e.g., hierarchy vs networks), participation structures (e.g., top-down vs collaborative design), and the use of digital systems (e.g., automation, transparency, feedback). This GPS tool was applied to twelve completed reform projects (P1–P12) implemented between 2014 and 2024, each supported by international donors, including GIZ, USAID, and the European Commission, among others. Each project was scored based on a thorough review of its key documentation: design logics, project plans, evaluations, monitoring reports, and official donor summaries. Documents were coded using an interpretive framework aligned with recent research on public sector digitalisation and hybrid governance (Hodgson et al., 2019; Cataldi, 2024). The scoring did not aim for perfect objectivity but rather for systematic, cross-case pattern recognition based on institutional attributes and governance intentions reflected in project artefacts. This interpretive logic is intentional. It directly counters the critique noted by Pevcin (2014) in the context of local governance, who shows that depending on the model used in technical efficiency scores, results can diverge significantly and may not fully reflect institutional complexity. Applying the same caution, our GPS tool was designed to avoid surface-level indicators that could mask the very governance fragmentation this paper investigates.

To complement the document analysis and verify GPS scores, twelve expert interviews were conducted with senior civil servants, donor representatives, and implementation advisors directly involved in the respective projects. Interviews were conducted between September and October 2025. Interviews lasted 45-70 minutes and followed a semi-structured format, focusing on governance goals, political constraints, digital tools, and perceived sustainability. This allowed the analysis to capture both formal design elements and practical implementation experiences. Interviews were used to help contextualise variations in scoring and to provide insights into informal practices not visible in written records. This approach of using double-sources aligns with recommendations in interpretive public administration research, which emphasise the value of combining institutional artefacts with practitioner narratives (Yanow & Schwartz-Shea, 2021; Patton, 2015).

The following section presents the findings from twelve externally supported public sector reform projects implemented in Kosovo between 2014 and 2024.

The analysis is based on project documentation and twelve semi-structured interviews with donor representatives, government officials, and project staff. The aim is to assess how these reforms reflect or diverge from key governance paradigms: New Public Management (NPM), New Public Governance (NPG), and digital governance. The data are organised in four parts: (1) aggregate governance patterns, (2) project-level scores and variation, (3) insights from interviews, and (4) additional indicators that help explain digital use, participation type, and strategy alignment.

This methodology provides several strengths. First, it integrates structured comparison with interpretive insight, which is essential for studying reforms in which policy goals, stakeholder influence, and institutional legacies interact. Second, the GPS framework enables explicit mapping of governance paradigms across diverse projects, offering clarity in otherwise fragmented data landscapes. Third, interview narratives provide depth, allowing reflection on implementation realities that may not appear in official documentation. Finally, combining qualitative scoring with practitioner validation enhances the robustness of interpretation and reduces researcher bias. Nonetheless, limitations must be acknowledged. Document-based scoring tends to reflect intended design more than lived practice. While triangulation across sources and interview data helps to mitigate this, full accuracy cannot be guaranteed. The sample focuses on externally funded projects with digital components, which may not fully reflect domestically initiated reforms or traditional bureaucratic projects. Additionally, interviews were selective in number and scope, serving to illustrate rather than exhaustively explain project dynamics.

Projects were selected through purposive sampling to ensure variation across donors, sectors and governance designs. Selection was also informed by data accessibility and relevance to national strategic objectives. All projects involved significant donor funding and contained a digital systems component, even if limited in scale. This enabled systematic comparison across cases while maintaining analytical focus. Data analysis followed a structured, interpretive logic. Rather than numerical aggregation, the GPS tool facilitated within-case and cross-case thematic comparison. This approach helps identify governance patterns, contradictions between paradigms, and how digital tools either reinforce or weaken the dominant reform logic. The analysis was designed not to produce general laws, but to develop grounded insights into how governance ideas are embedded and operationalised in a projectified, transitional public sector (Pollitt & Bouckaert, 2017).

Table 1: Evaluated projects

Code	Project / Reform Title	Donor / Financing Modality	Years (Start–End)	Budget (€)	Policy Area / Main Objective	Digital System(s) Used
P1	Strengthening Statistical System of Kosovo	SIDA	2015-2019	35,000,000.00	Governance	Gender mainstreaming e-platforms, internal compliance tracking tools

Code	Project / Reform Title	Donor / Financing Modality	Years (Start–End)	Budget (€)	Policy Area / Main Objective	Digital System(s) Used
P2	Kosovo Threshold	MCC	2017-2021	49,000,000.00	Governance	e-Procurement System, Case Management for Courts, Asset Declaration System
P3	Kosovo Energy Efficiency and Renewable Energy	World Bank	2014-2020	31,000,000.00	Governance	Monitoring system for energy efficiency investments (basic MIS), no major digital platform
P4	ALLED II	EU	2017-2022	11,000,000.00	Education	Digital tracer studies, career guidance platforms, and labour market info system
P5	Active Labour Market 2	UNDP	2019-2023	4,200,000.00	Education	Employment management information system (MIS), data dashboard for policy coordination
P6	Kosovo Digital Economy	World Bank	2018-2023	20,000,000.00	Digitalization	Broadband Mapping Tool, Online Services Registry, Digital Skills Training LMS
P7	Youth, Employment and Skills	GIZ	2020-2023	7,000,000.00	Education	VET school database, online learning platform pilots
P8	Fit for Jobs	GIZ	2021-2024	6,500,000.00	Education	Company-student matching portal (pilot), digital teacher training materials
P9	Support to Kosovo Assembly	EU	2014-2018	1,800,000.00	Governance	E-legislation drafting support tools, internal communication platform (pilot only)
P10	Strengthening Public Finance Management (phase 2)	EU	2022-2024	2,500,000.00	Governance	Integration with e-procurement, budget execution reporting system

Code	Project / Reform Title	Donor / Financing Modality	Years (Start–End)	Budget (€)	Policy Area / Main Objective	Digital System(s) Used
P11	Support to VET reform in Kosovo	LuxDev	2017-2024	10,000,000.00	Education	Digital Marketing, Career Orientation, Accounting Tools
P12	ESVETPRO	EU	2019-2023	3,000,000.00	Education	Tracer Study, Recognition of Prior Learning

Source: GPS, authors' presentation

This paper provides an analysis of 12 donor-funded reforms and projects implemented in Kosovo from 2014 to 2024. The contributing donor institutions are the European Union (4), the World Bank (2), GIZ (2), LuxDev (1), SIDA (1), MCC (1), and UNDP (1). These projects were purposefully selected to represent central governance areas and the major organisations providing funding. The data utilised for this study originate from three categories of sources: (i) the official project documents (including design specifications, logical frameworks, monitoring materials, and evaluations); (ii) relevant administrative files; and (iii) twelve semi-structured interviews conducted with high-level personnel. All interviewees remain anonymous; any quotations used are coded by project and individual role. The final selection of the twelve cases relied on several requirements: the availability of comprehensive documentation, assured access to key informants for interviews, and direct relevance to the public sector. Additionally, the portfolio was designed to incorporate variation in donor participation and sectoral allocation (governance, education, digital economy).

A governance profiling tool with 20 indicators is applied, capturing NPM/control and NPG/PV coordination features (≈10 indicators per dimension). Each project was scored on 20 indicators using a 0–2 scale (0 = absent, 1 = partial, 2 = strong). Half-points (e.g., 1.5) were allowed when evidence was mixed. A short rubric defined what counts as 0, 1, or 2 for each indicator. The coder scored all cases; a second coding round was applied to 3 cases to calibrate judgments; then discrepancies were discussed and resolved. Every score is traceable to a document page or interview note.

For each project:

- NPM score = mean of the ≈10 NPM indicators.
- NPG score = mean of the ≈10 NPG/PV indicators.
- Balance = NPG − NPM (negative → control-heavy; positive → coordination-heavy).

The study also records three outcome proxies: Continuity @12 months (presence of outputs one year after close), Institutionalisation (0–2), and Ownership (1–5), using brief anchors in the CodeBook. To avoid subjective labels, the dominant digital role per project is classified by rule:

- Coordination/Workflow if at least two coordination items score 2 and

control items are limited;

- Otherwise, Reporting/Control.

Participation was voluntary, with informed consent recorded before each interview. No personal identifiers are reported; quotes are coded by project and role. Notes and transcripts are stored on an encrypted drive accessible only to the authors and will be deleted 12 months after publication.

Despite these limitations, this methodology is suitable for exploring how governance paradigms, project logic, and digital systems shape reform outcomes. It offers a grounded, multi-layered perspective on public administration transformation in fragile and donor-dependent contexts.

4 Results

Across 12 projects, the average NPM score is 1.63, the average NPG/PV score is 1.43, and the mean Balance is −0.21 (NPM-leaning). Using a simple ±0.20 band, 6 cases are NPM-leaning, 5 are balanced, and 1 is NPG-leaning. Under the classification rule, 11/12 projects' digital tools serve reporting/control rather than day-to-day coordination. Continuity is high in most cases, while institutionalisation is mid-level (≈1.5/2) and perceived ownership is moderate (≈3.3/5).

Table 2 shows the average scores across six governance dimensions. The scores show a structural choice: donors focus on technical visibility (Digital Tools: 2.3) and box-checking participation (Stakeholder Engagement: 2.1), while systematically leaving out the necessary work of making reforms stick (Sustainability: 1.6; Ownership: 1.5). Monitoring and evaluation frameworks are common, but mostly focused on formal reporting instead of learning or improvement. These patterns suggest that while external projects bring technical tools and participatory language, deeper institutional embedding, such as long-term ownership and sustainability, is often missing. This supports earlier findings that project-based reforms tend to deliver outputs without anchoring them in the broader public administration system (Jacobsen, 2022; Pollitt & Bouckaert, 2017).

Table 2: Average Governance Paradigm Scores across 12 projects

Governance Dimension	Mean Score
Goal-setting logic	1.8
Stakeholder engagement	2.1
Digital tool usage	2.3
Monitoring & Evaluation	1.7
Sustainability mechanisms	1.6
Ownership and control	1.5

Source: GPS, authors' presentation

Table 3 presents detailed scores for each project across the six governance dimensions. The total scores range from 7.2 to 13.7. Projects like P8, P4, and P12 reflect stronger alignment with NPG principles, including participatory design, flexible implementation, and integrated digital systems. In contrast, P2, P7, and P11 are closer to a classic NPM logic, which emphasises control and KPIs, with limited participation or local ownership. Most projects fall between these two extremes, exhibiting hybrid features. For example, several projects combine formal consultation processes with strict donor reporting requirements, resulting in a fragmented implementation logic. This confirms previous research on governance hybridisation in aid-dependent states (Cataldi, 2024; Hodgson et al., 2019).

Table 3: Project Governance Scores by dimension

Project	Goal-setting	Stakeholder Engagement	Digital Tools	Monitoring & Evaluation	Sustainability	Ownership	Total Score
P1	2.3	2.7	2.3	2.0	1.3	1.5	12.0
P2	1.3	1.3	1.7	1.0	1.3	1.3	7.8
P3	2.0	1.7	2.7	1.7	1.3	1.3	10.7
P4	2.0	2.3	2.3	2.0	2.0	1.7	12.3
P5	2.0	1.7	2.0	1.7	1.3	1.3	10.0
P6	1.7	2.0	2.3	1.7	1.7	1.3	10.7
P7	1.7	1.3	2.3	1.7	1.3	1.3	9.6
P8	2.3	2.3	2.7	2.3	2.0	2.0	13.7
P9	1.7	1.7	2.0	1.3	1.3	1.3	9.3
P10	2.0	1.7	2.0	1.7	1.3	1.3	10.0
P11	1.3	1.3	1.3	1.3	1.0	1.0	7.2
P12	2.0	2.3	2.3	1.7	1.7	1.7	11.7

Source: GPS, authors' presentation

The semi-structured interviews added significant depth to document analysis by providing practical insights from those involved in the project implementation. Interviewees confirmed that stakeholder participation varied considerably across projects. In cases like P4, P8, and P1, there was evidence of engagement through joint steering committees and active involvement in co-designing the project activities. These mechanisms enabled stakeholders, including government representatives, to influence project direction and adapt activities to changing needs. In the P7 project, the working groups were described as "*functional and regular: coordinating project needs with VET reform implementation*". In contrast, in P12, a senior manager recalled "*working groups were formed but never worked… 1-2 workshops producing nothing*" (Interviews, P7, P12, 2025).

In contrast, projects such as P2, P7, and P11 were primarily driven by top-down donor decisions, with limited or symbolic involvement from local actors. Flexibility also differed: Projects P1 and P6 offered opportunities for

adjustments during implementation, especially in response to context-specific challenges. These projects allowed implementers to shift focus, revise targets, or include additional partners. However, other projects, particularly P2 and P11, followed rigid logic with fixed outputs, predefined timelines, and little room for adjustment. Digitalisation emerged as a key component in many projects, but its actual use was uneven. Interviewees involved in P6, P8, and P12 described how digital tools supported coordination across ministries and agencies. In these cases, platforms were developed, tested, and utilised by stakeholders. Conversely, several projects introduced digital systems that were never adopted due to legal constraints, lack of maintenance, or low institutional buy-in. Ownership and sustainability remained consistently weak across most projects. Only a few, such as P4 and P6, saw local institutions assume leadership roles and stay engaged after the project formally concluded. A civil servant from the P11 Project Implementation Unit explicitly expressed this absence of genuine ownership, stating: "*We had no say in design…just reporting duties*." This comment highlights a broken chain of responsibility that disappears entirely once donor funding ceases. This limited their capacity to sustain project outputs or apply lessons learned to future reforms, especially if the project was not fully aligned with national strategies, thereby reducing opportunities for continuity. Feedback mechanisms also showed differences: P4 and P8 distinguished themselves by incorporating user feedback through surveys and learning loops, which influenced project adjustments. Elsewhere, consultation processes were either formal or conducted late in the project cycle, with limited impact on outcomes. Respondents emphasised this fragmentation themselves. "*Reforms are fragmented across donors… No one's talking to each other*," said one senior advisor (Interview, MA, 2024). Others echoed that "*each project has its own rules, tools, and logic*," reinforcing institutional silos rather than integration (Interview, JA, 2024). These findings reinforce existing concerns that participatory mechanisms are often performative rather than transformative. This aligns with Durnik's (2012) findings, which show that participatory frameworks often serve as procedural checkboxes rather than genuine mechanisms for citizen empowerment, particularly in systems with low administrative responsiveness.

Table 4: Summary of interview insights across governance dimensions

Governance theme	Interview-Based insights
Stakeholder Participation	Strong in P4, P8, and P1 (joint steering, co-creation); minimal in P2, P11, P7 (top-down design, exclusion of municipalities, no user consultation)
Project Flexibility	Evident in P1 and P6 (adaptive roll-out); constrained in P2 and P11 due to donor-driven timelines and pre-set outputs
Digital Tools	Systems in P8, P12, and P6 used to coordinate multi-agency processes; in P2 and P11 digital platforms were "introduced but unused" due to lack of legal anchoring.

Ownership	Present in P4 and P6 (PMO or ministry co-leadership); absent in P2 and P11 ("we had no say in design, just reporting duties").
Sustainability	Present in P4 and P6 (PMO or ministry co-leadership); absent in P2 and P11 ("we had no say in design, just reporting duties").
Feedback Mechanisms	Well-used in P4 and P8 (surveys, iteration); dismissed in P2 and P11 ("consultations were symbolic, not influencing anything").

Source: GPS, authors' presentation

To strengthen the comparative assessment, three cross-cutting indicators were introduced: the intensity of digitalisation, the type of stakeholder participation, and the degree of strategic alignment with national priorities. These indicators help explain variations in project performance beyond the core GPS dimensions. Digitalisation levels were highest in P8 and P12, where digital tools were not only developed but also integrated into workflows and maintained post-project. These tools were generally accessible, user-oriented, and included features for real-time monitoring or stakeholder interaction. In contrast, several projects developed platforms that remained inactive due to lack of legal support, inadequate infrastructure, or resistance from host institutions.

Stakeholder participation was most robust in projects where beneficiaries were engaged not only as informants but as partners in decision-making. P4 and P8 were the clearest examples of participatory governance, where stakeholders influenced key decisions and implementation approaches. Most other projects, however, involved stakeholders only at the beginning or during final validation sessions, with limited influence on content or timing. This reflects a broader issue in externally driven reforms where participation is procedural rather than substantive.

Strategic alignment also varied. Projects like P4 and P8 were clearly linked to national strategies and sectoral plans, which increased their legitimacy and continuity. These projects were more likely to be integrated into ministries' or agencies' work after the projects ended. In contrast, projects such as P2 and P11 operated with minimal reference to local strategic frameworks, leading to weak institutional uptake and limited sustainability.

Table 5: Additional indicators: Digital tools, Participation type, Strategy alignment

Project	Digital Components	Stakeholder Participation	Strategic Alignment
P1	2	Consultative	Moderate
P2	1	None	Low
P3	2	Consultative	High

Project	Digital Components	Stakeholder Participation	Strategic Alignment
P4	3	Decision-making	High
P5	2	Consultative	Moderate
P6	2	Consultative	Moderate
P7	2	None	Low
P8	5	Decision-making	High
P9	1	Consultative	Moderate
P10	2	Consultative	Moderate
P11	1	None	Low
P12	4	Consultative	High

Source: GPS, authors' presentation

Together, these indicators support the overall argument that reform effectiveness depends not only on the presence of tools or procedures but on how well they are aligned with national systems, governance logic, and stakeholder capacities. Without this alignment, even well-designed reforms risk becoming isolated interventions with limited long-term impact.

5 Discussion

This paper reports findings in the order of the research questions: the NPM–NPG balance (R1), the role of digital tools (R2), and their relation to ownership, continuity, and institutionalisation (R3). The findings from the twelve externally supported reform projects confirm that donor-funded initiatives in Kosovo follow diverse and hybrid governance logic, often situated between the managerial ideals of New Public Management (NPM) and the collaborative features of New Public Governance (NPG). The academic texts often present the New Public Governance (NPG) approach as a solution to fix the problems of the too-strict New Public Management (NPM) framework (Osborne, 2006; Klijn & Koppenjan, 2016). However, our study in Kosovo reveals a different pattern. Here, the reform ideas, or paradigms, are not being introduced in a structured order (they are not sequenced), and they do not work together effectively (they are not synergised). Instead, they seem to be just piled up on top of each other without a clear plan (they are arbitrarily layered). For example, projects frequently include the strict performance indicators that belong to NPM, while also use the participatory design of NPG. This mixing does not happen because of smart design. It happens because they must meet the separate rules and requirements of different donor organisations. This situation supports the criticism made by Pollitt and Bouckaert (2017), who argue that this kind of "layered governance" can simply be a way to hide a fundamental lack of coordination and sense. For instance, people we spoke to in the P7 project clearly described having to handle both planning-

focused capacity building and rigid performance targets. As one team member explained: "*We had to report quarterly KPIs, but also organise roundtables… these were not coordinated*." (Interview, JA, 2025).

At the same time, while digital tools are present in nearly all cases, they are deployed inconsistently and often remain disconnected from institutional ownership. This reflects a broader issue in transition settings where digitalisation becomes a symbolic rather than a structural element of reform (Kmezić, 2020; Cataldi, 2024). This analysis challenges the common idea that using digital technology (digitalisation) automatically makes governments more efficient (see Cataldi, 2024; Maulana et al., 2024). Instead, our interviews suggest that these new digital platforms often serve more as tools for donor control than as means to build local capacity and knowledge. For example, in the P12 project, local staff could not even access "AlphaBase," the digital system itself. This lack of access seriously undermined institutional learning (Interview, HB, 2025). This finding confirms warnings in academic literature that digital reforms in places with weak institutions (fragile settings) can actually strengthen centralised power and serve the donor's logic rather than local needs (Cordella & Tempini, 2015). This is especially true when digital tools are introduced as technical fixes without being matched to existing local work processes. One advisor summarised the problem directly: "*The tool worked, but not for us; it worked for reporting to Brussels*" (Interview, AP, 2025).

Projects such as P4, P8, and P12 reflected higher alignment with NPG values, particularly in their use of co-creation mechanisms, stakeholder steering structures, and digital platforms designed for interaction, not just reporting. These projects were often integrated with national strategies and allowed for adaptive management approaches. This reflects findings in the wider literature that NPG-aligned reforms tend to foster ownership and flexibility in governance systems, particularly when digital tools are used as enablers of networked service delivery (Osborne, 2020; Kuitert et al., 2024). In Kosovo, P8's real-time dashboard system, supported by joint steering with the Ministry of Finance, is an example of such alignment. It allowed actors to monitor reform uptake across agencies, reflecting a more embedded and sustainable reform logic. In contrast, projects such as P2, P7, and P11 remained grounded in a classical NPM approach. They focused on pre-defined deliverables, linear timelines, and rigid monitoring tools. These interventions were praised for their technical efficiency but lacked deeper institutional engagement. In P2, for instance, a procurement reform system was introduced, but post-project interviews showed that the relevant agency did not continue using the system due to lack of training, legal backing, and internal ownership. This supports Pollitt and Bouckaert's (2017) observation that externally managed NPM-style reforms often deliver outputs without embedding capabilities for long-term change.

Across the sample, digitalisation was present in all twelve projects, yet its usage showed major differences. In NPM-aligned projects, digital tools were often developed for upward accountability i.e., reporting to donors and tracking KPIs. In contrast, in NPG-oriented projects, digital platforms were integrated into decision-making and inter-agency coordination. Projects such as P12 used digital applications to share budget data across ministries and

municipalities, increasing transparency and mutual learning. These practices reflect the growing body of work calling for "connected governance" rather than isolated data portals (Gil-Garcia et al., 2020).

A protracted problem of institutional anchoring made several technically functional platforms useless. They were simply de-coupled from existing administrative structures and fell into disuse due to a lack of formal policy mandate or budget continuity post-project. This reflects a deeper contradiction in Kosovo's governance structure, where externally driven reforms tend to build parallel systems rather than strengthen existing administrative structures (Muharremi, 2020). For example, in P11, a digital tool for tracing the graduates of Kosovo VET sector was never adopted because of conflict with an existing legacy system maintained by a different ministry (Interview, BSh, 2025).

A related issue is ownership and sustainability. Many projects, especially those influenced by NPM, were delivered by consultants or parallel teams and disengaged after project closure. While these projects may have met short-term donor targets, they failed to develop institutional memory or strengthen systemic capabilities. This concern is echoed in Džankić et al. (2020), who argue that reliance on donor-led reforms creates cycles of reform fatigue, dependency, and "implementation without institutionalisation." In contrast, NPG-oriented projects (notably P4 and P8) demonstrated greater sustainability, as they were connected to ongoing national strategies, involved domestic institutions from the outset, and incorporated mechanisms for post-project continuation. This supports the argument that participatory and embedded reforms have a stronger chance of institutional integration (Elbasani, 2018). However, these cases were exceptions rather than the norm. Most reforms still adhered to a projectified approach, characterised by short-term focus, lack of cross-project learning, and parallel systems. Even where digital tools were designed to be "scalable," they remained isolated due to the absence of cross-agency mandates or standardised data frameworks. This aligns with recent critiques of project-based public management in Western Balkan countries, where digital and governance reforms are often disconnected from long-term state-building agendas (Vishinska, 2023).

A tension also arose between the logic of control and the logic of learning. NPM-driven projects, by emphasising control through KPIs and deliverables, left little space for institutional learning or reflexivity. NPG-aligned projects, on the other hand, struggled with accountability gaps due to soft management structures and unclear performance frameworks. As shown in a comparative work by Maulana et al. (2024), collaborative digital governance efforts often fail when role clarity and accountability are lacking, a problem also observed in Kosovo's reform trajectory. Without strong anchoring in institutional mandates, even participatory reforms risk becoming disjointed. Kosovo's public administration often lacked the absorptive capacity to fully manage either model. This confirms that governance paradigms should not be imposed rigidly but tailored to the context (Christensen & Lægreid, 2020).

Finally, the empirical data raise concerns about the uneven digital maturity across institutions. While some ministries have adopted new tools and integrated them into daily operations, others lack basic infrastructure, staff skills, or legal authority to implement reforms. This digital divide reinforces

structural fragmentation and limits the potential for digital governance to act as a unifying force. For digital tools to support either NPM or NPG paradigms, they must be embedded in an institutional ecosystem that includes policy alignment, budget continuity, and inter-organisational coordination (OECD/SIGMA, 2022).

6 Conclusions

This paper examined twelve donor-funded reform projects in Kosovo to understand how they align with the principles of New Public Management (NPM), New Public Governance (NPG), and digital governance. The analysis addressed three main questions. First, regarding governance logic, most initiatives reflected a mixed approach, though managerial features typical of NPM were more dominant. Participatory or collaborative elements existed but were often limited to formal consultations that had little influence on the design or decision-making. Around half of the projects were clearly driven by control and performance mechanisms rather than partnership-oriented practices. Second, digital tools were present across nearly all projects but primarily served as monitoring and donor reporting tools. Only a few initiatives, such as Projects 8 and 12, used digital platforms as part of coordination, communication, or service delivery processes. Third, local ownership remained weak in most cases. Projects managed externally or detached from public institutions rarely continued once funding ended. More sustainable results emerged when national institutions were involved from the start and played a role in steering implementation.

The analysis shows that the projects included in this paper largely reflect an NPM-leaning logic, while NPG and digital elements appear in a more selective and uneven way. This confirms the initial expectation that governance models in donor-funded reforms are layered rather than clearly coordinated or sequenced. The paper`s contribution lies in showing how these mixed paradigms shape implementation in practice and in offering a structured way to assess them through a GPS tool. Methodologically, the paper combines structured document-based scoring with expert interviews. This operationalises triangulation for projectified reforms, where formal design and practice often diverge. The approach strengthens the interface by validating GPS scores against practitioner accounts and by capturing informal coordination that project documents rarely record. The GPS tool provides a replicable coding logic to map hybrid governance elements (NMP, NPG, digital governance) across heterogeneous projects while retaining case-level interpretation. Future work can extend the framework through longitudinal follow-ups after project closure, denser within-project interviewing, and inter-coder reliability checks for GPS scoring. This is particularly relevant in donor-driven reform settings where project documentation reflects compliance signals, while interviews capture coordination workarounds and institutional bypass. At the same time, the study has limits. Some project files were less complete than others, interview coverage was inconsistent — interviewees came from the implementation unit in some projects and from institutions in others — and the analysis relies on interpretive scoring, which may not fully capture all institutional nuances. These limitations point to next steps, including a broader

comparison within the country and with other Western Balkan cases, and a closer examination of institutional behaviour inside ministries. Finally, the findings suggest several institutional implications: reforms should be better anchored in existing structures, digital systems should be formally integrated into daily routines rather than used only for reporting, and donors should work towards reducing parallel arrangements so that reforms can build more stable, long-term capacities.

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Digital Mapping of Global Research on Fiscal Consolidation: A Bibliometric Analysis

Review article

Biljana Stanivuk[1], Vesna Petrović[2], Biljana Kovačević[3]

ABSTRACT

This paper provides a comprehensive bibliometric overview of the scientific research literature on fiscal consolidation based on 276 publications indexed in the Web of Science Core Collection over the period 2006–2024. The main objective is to identify dominant research trends, influential authors, thematic clusters, and patterns of international scientific collaboration in the field of fiscal consolidation. The study applies quantitative bibliometric techniques using the Bibliometrix package in R and network visualization through VOSviewer. The analysis encompasses citation analysis, co-authorship networks, author co-citation structures, keyword co-occurrence, and three-field mapping of references, authors, and research themes. The results reveal a strong cyclicality in scientific output, closely related to major economic crises, particularly after 2010. The most influential research clusters focus on the macroeconomic effects of fiscal consolidation, public debt sustainability, institutional and political determinants of fiscal policy, and fiscal-monetary policy interactions. The central role of authors such as Alesina and Blanchard confirms the existence of dominant theoretical and empirical schools within the literature. Furthermore, the spatial analysis of collaboration highlights a pronounced dominance of European and Anglo-Saxon countries, while developing and transition countries remain underrepresented. The findings emphasize the heterogeneity and multidimensional nature of fiscal consolidation as a research field and provide a structured foundation for future

1 *PhD Candidate, University of Belgrade, Faculty of Economics, 11000 Belgrade, Serbia. Scientific affiliation: Faculty of Economics University of Belgrade; Faculty of Business Economics Bijeljina, University of East Sarajevo. Phone: +387 65 673 202 . E-mail: biljana.stanivuk@fpe.ues.rs.ba*

2 *Associate Professor, University of East Sarajevo, Faculty of Business Economics Bijeljina, Semberskih ratara 1E, 76300 Bijeljina, Bosnia and Herzegovina. Scientific affiliation: Faculty of Business Economics Bijeljina, University of East Sarajevo. Phone: +387 65 526 350. E-mail: vesna.petrovic@ fpe.ues.rs.ba*

3 *Associate Professor, University of East Sarajevo, Faculty of Business Economics Bijeljina, 76300 Bijeljina, Bosnia and Herzegovina. Scientific affiliation: Faculty of Business Economics Bijeljina, University of East Sarajevo. Phone: +387 65 573 491. E-mail: biljana.kovacevic@ fpe.ues.rs.ba*

empirical studies, particularly in underexplored institutional contexts such as the Western Balkan region.

***Keywords**: Fiscal consolidation, Public debt, Fiscal policy, Bibliometric analysis, Economic growth*

***JEL classification**: E62, H62, H63, C10, O40*

1 Introduction

Contemporary economic literature increasingly focuses on issues of fiscal policy, public finance sustainability, and the long-term effects of fiscal consolidation, particularly in the aftermath of the global financial crisis of 2008, the euro area sovereign debt crisis, and the COVID-19 pandemic. In this context, fiscal consolidation has emerged as one of the key instruments for stabilizing public finances, reducing budget deficits, and establishing a sustainable public debt trajectory (Stanivuk, 2023). Despite a growing volume of empirical studies, the academic debate on the effects of fiscal consolidation remains heterogeneous, with pronounced differences in results depending on the applied methodology, time horizon, institutional framework, and the structure of implemented fiscal measures.

Within such a research environment, there is a strong need for a systematic overview of the development of scientific thought in this field, as well as for the identification of the most influential authors, dominant thematic trends, and major research streams. Bibliometric analysis represents a methodological response to this need, as it enables a quantitative mapping of the structure of scientific production through the analysis of publications, citations, co-citations, and collaboration networks among authors and institutions.

The aim of this paper is to provide a comprehensive overview of global research trends in the field of fiscal consolidation by applying a bibliometric approach to a sample of scientific publications indexed in the Web of Science database over the period 2006–2024. Special emphasis is placed on identifying dominant thematic clusters, the most influential authors, the most highly cited papers, and patterns of international scientific collaboration.

The central research question of this study is formulated as follows:

How have thematic, authorship, and methodological trends in scientific research on fiscal consolidation evolved over time, with particular reference to Europe?

The scientific contribution of this paper lies in the systematic mapping of the structure of the literature on fiscal consolidation, the identification of key research schools, and the detection of the evolution of dominant research themes. The findings provide a reliable foundation for future empirical research in this field and serve as a valuable guide for researchers when selecting relevant theoretical and methodological approaches.

The paper is structured as follows: the second section presents a review of the relevant literature and discusses the role of bibliometric methods in contemporary research; the third section outlines the methodological framework and data selection criteria; the fourth section presents the empirical analysis and the results of the bibliometric mapping; the fifth section discusses the results in a broader macroeconomic context; and the final section provides conclusions, limitations, and recommendations for future research.

2 Literature review

In contemporary scientific research, the literature review represents the fundamental basis for understanding the existing state of knowledge, identifying research gaps, and directing future research efforts. While traditional literature review relies primarily on the qualitative interpretation of previous studies, quantitative approaches have gained increasing importance over recent decades, among which bibliometric analysis occupies a particularly prominent position (Aria & Cuccurullo, 2017; Junquera & Mitre, 2007).

Bibliometrics comprises a set of methods used for the quantitative analysis of scientific publications, citation patterns, and the structure of scientific production through the application of statistical and network-based techniques (Pritchard, 1969; Garfield, 2009). This approach enables the identification of dominant research streams, the most influential authors and institutions, as well as insights into how a particular scientific field evolves over time. Unlike the narrative literature review, bibliometric analysis provides a higher degree of objectivity, facilitates visualization of results, and enables the examination of relational structures within the scientific community.

In the field of fiscal consolidation, the bibliometric approach is especially relevant because this topic has developed across diverse macroeconomic and institutional contexts, ranging from advanced economies to transition and developing countries. A substantial body of literature has examined the macroeconomic effects of fiscal consolidation, particularly its impact on economic growth, employment, and public debt sustainability (Alesina & Ardagna, 2010; Alesina et al., 2015; Guajardo et al., 2014; Blanchard & Leigh, 2013). These studies demonstrate that the effects of consolidation measures depend critically on their composition, timing, and the prevailing macroeconomic environment.

Several authors emphasize the distinction between expenditure-based and revenue-based adjustment programs, arguing that consolidation based on expenditure cuts tends to be less contractionary and more sustainable in the long run (Alesina & Perotti, 1997; Alesina & Ardagna, 1998; Afonso & Jalles, 2012). In contrast, Keynesian-oriented studies stress the presence of significant fiscal multipliers, especially in periods of economic downturn, suggesting that consolidation measures may exert strong negative short-term effects on output and employment (Christiano et al., 2011; Corsetti et al., 2012; Blanchard & Leigh, 2013).

Beyond macroeconomic effects, a growing strand of literature focuses on the institutional and political economy dimensions of fiscal consolidation.

These studies highlight the importance of fiscal rules, political cycles, and governance quality for the success of consolidation programs (Debrun et al., 2008; Wyplosz, 2012; Bohn, 1998, Stanivuk 2020). The credibility of fiscal institutions and the design of budgetary frameworks are frequently identified as key determinants of long-term fiscal sustainability, particularly in the context of high public debt.

In addition to global studies, a substantial body of research originates from regional and national contexts, which are often not fully covered by international citation databases. This is particularly relevant for transition economies and emerging markets, where institutional constraints and structural characteristics differ significantly from those in advanced economies (IMF, 2010; World Bank, 2018). For this reason, scholarly practice increasingly combines bibliometric and traditional narrative approaches in order to achieve both quantitative objectivity and qualitative depth of analysis.

In this regard, the present study relies primarily on bibliometric analysis, as its core research tool, while the obtained findings are interpreted within a broader framework of theoretical and empirical contributions in the field of fiscal policy. Such an integrated approach ensures a balanced assessment between quantitative mapping of scientific production and qualitative understanding of the content and scientific messages conveyed by the most influential studies.

3 Conception of analysis

The methodological framework of this study is based on the application of bibliometric analysis as a quantitative research approach used to examine the structure, dynamics, and interconnections of scientific publications in the field of fiscal consolidation. Bibliometric methods enable a systematic evaluation of large bodies of scientific literature through statistical and network-based indicators, providing insights into research trends, intellectual structures, and collaboration patterns (Aria & Cuccurullo, 2017; Garfield, 2009).

The empirical dataset was obtained from the Web of Science Core Collection, one of the most comprehensive international citation databases widely used in bibliometric research (Mongeon & Paul-Hus, 2016). The selection of scientific publications was conducted using a predefined search strategy based on a combination of thematic keywords related to fiscal consolidation and public finance. The primary search terms included: fiscal consolidation, fiscal adjustment, public debt, fiscal deficit, public debt sustainability, fiscal policy, public revenues, and public expenditures.

The initial search, conducted using a predefined combination of keywords related to fiscal consolidation and public finance, yielded a total of 874 records. In order to ensure the analytical relevance and consistency of the final sample, a multi-stage filtering procedure was applied. The search strategy was based on a predefined combination of thematic keywords related to fiscal consolidation and public finance, including: “fiscal consolidation” OR “fiscal adjustment” AND “public debt”, “fiscal deficit” OR “public debt sustainability” AND “fiscal policy” AND “public revenues” AND “public expenditures”. The inclusion criteria comprised publications indexed in WoSCC, published in

English, covering the period 2006–2024, and classified as article, proceeding paper, book, or book chapter. Additional inclusion criteria referred to subject relevance, which was ensured by restricting the dataset to the Web of Science categories Economics, Fiscal Policy, and Public Economics, as well as to the meso-level citation topic Economics and the micro-level citation topics Fiscal Policy, Monetary Policy, Economic Growth, and Tax Evasion. Since the study is focused on the European research context, the final sample was additionally limited to publications classified under the country/region filter Europe and indexed in the Social Sciences Citation Index (SSCI). The exclusion criteria therefore included records in other languages, publications outside the selected time span, document types not consistent with the scope of the study, records outside the selected subject categories and citation topics, publications not related to Europe, and records not indexed in SSCI. After the application of a multi-stage filtering procedure based on language, document type, thematic relevance, and index coverage, the final sample consisted of 276 scientific publications covering the period from 2006 to 2024.

Since the search procedure involved a structured retrieval process within a single bibliographic database, the dataset was additionally checked for duplicate records during the data-cleaning stage. Duplicate detection was performed by comparing titles, author names, publication years, and DOI information where available. This procedure was introduced in order to ensure the integrity and reliability of the final bibliometric corpus.

The selected time span, 2006–2024, was chosen in order to capture the evolution of scientific research on fiscal consolidation across several major phases of contemporary macroeconomic development. This period includes the pre-crisis years, the global financial crisis of 2008–2009, the euro area sovereign debt crisis, the period of post-crisis fiscal adjustment, and the more recent policy debates shaped by the consequences of the COVID-19 shock. Therefore, the chosen time frame provides a sufficiently broad and analytically meaningful basis for identifying thematic, authorship, and methodological trends in the European scientific literature on fiscal consolidation.

Data processing and bibliometric analysis were conducted using the Bibliometrix package in the R programming environment (RStudio), which provides a wide set of tools for descriptive and network-based bibliometric analysis (Aria & Cuccurullo, 2017). Network visualizations of authors, keywords, and collaboration patterns were additionally generated using VOSviewer, a specialized software designed for constructing and visualizing bibliometric networks (van Eck & Waltman, 2010).

The bibliometric analysis comprised the following key components:

- Citation analysis, used to identify the most influential publications and authors in the field (Garfield, 2009);
- Co-authorship analysis, aimed at examining patterns of scientific collaboration and international research networks (Newman, 2001);
- Author co-citation analysis, applied to detect intellectual linkages and dominant research schools within the literature (Small, 1973);
- Keyword co-occurrence analysis, employed to identify the main thematic

clusters and conceptual structures of the research field (Callon et al., 1991);

- Spatial analysis of international collaboration, used to assess the geographical distribution and connectivity of scientific production.

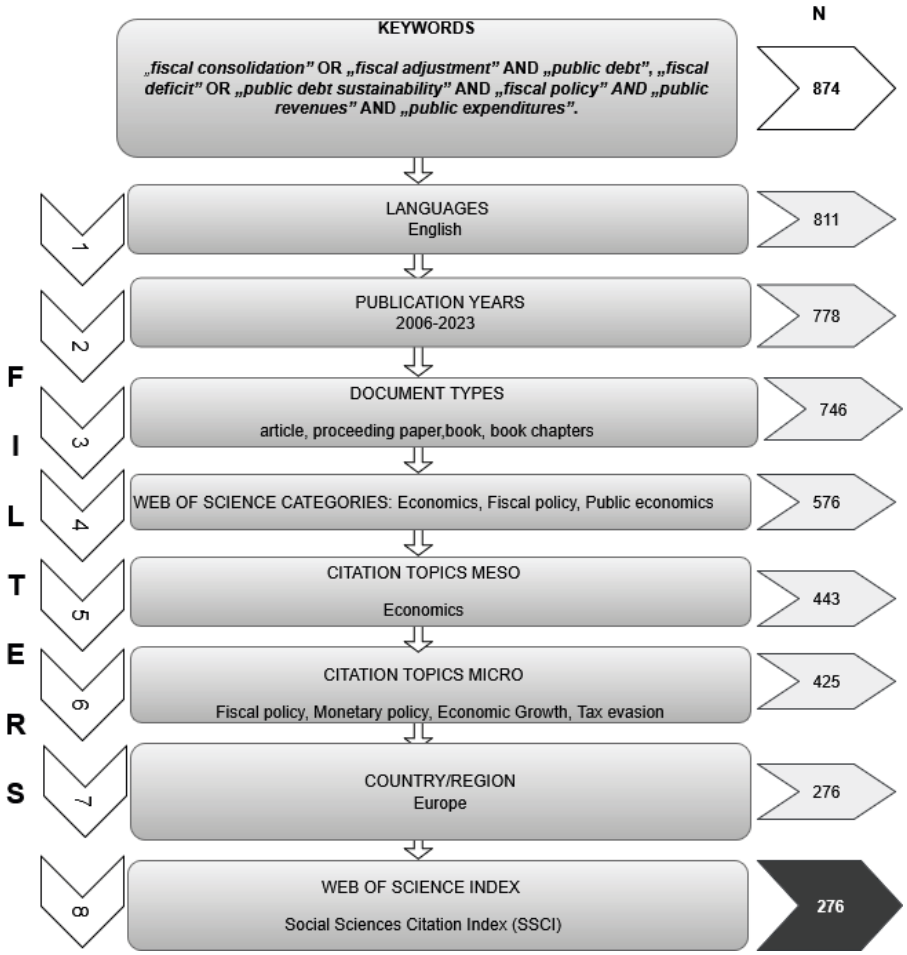
A specific segment of the methodological procedure involved the application of the Three-Field Plot (Sankey-type diagram), which simultaneously links the most cited references, the most influential authors, and the dominant research themes. This approach enables a multidimensional representation of the research field by integrating its referential, authorship, and conceptual dimensions within a single analytical framework (Cobo et al., 2011).

The results of the bibliometric analysis are presented through a combination of descriptive statistics, tables, and network visualizations. Their interpretation relies on the joint use of quantitative bibliometric indicators and qualitative economic reasoning, allowing for a comprehensive assessment of the development of scientific knowledge on fiscal consolidation and its main research directions.

4 Empirical data and analysis

The empirical part of this study is based on the bibliometric processing of a total of 276 scientific publications indexed in the Web of Science Core Collection over the period 2006–2024, which were selected from an initial pool of 874 records after a multi-stage filtering procedure. The filtering process included language restrictions, document type selection, thematic relevance, and index coverage, ensuring a high degree of consistency and relevance of the final dataset. Key components to be included in this analysis are citation analysis, co-authorship analysis, keyword analysis, and publication analysis (Kovačević & Božić, 2024).

Figure 1: Document screening and selection algorithm



Source: Authors

The descriptive characteristics of the analyzed dataset indicate a relatively mature and internationally interconnected research field. The sample comprises 141 distinct sources (journals, books, and proceedings), with an average document age of 7.93 years. The average number of citations per document amounts to 10.76, while the total number of references cited within the analyzed corpus reaches 8,394. A total of 566 authors contributed to the selected publications, of whom 62 authored single-author papers, whereas the average number of co-authors per document is 2.42. Of particular importance is the share of international co-authored publications, which accounts for 36.59%, indicating a high level of cross-country research collaboration in this field.

In terms of document structure, journal articles clearly dominate the sample, while a smaller number of publications appear as conference papers, book chapters, or early-access articles. This distribution suggests that fiscal consolidation is primarily developed and disseminated through peer-reviewed international journals.

Table 1: Descriptive overview of the selected data sources

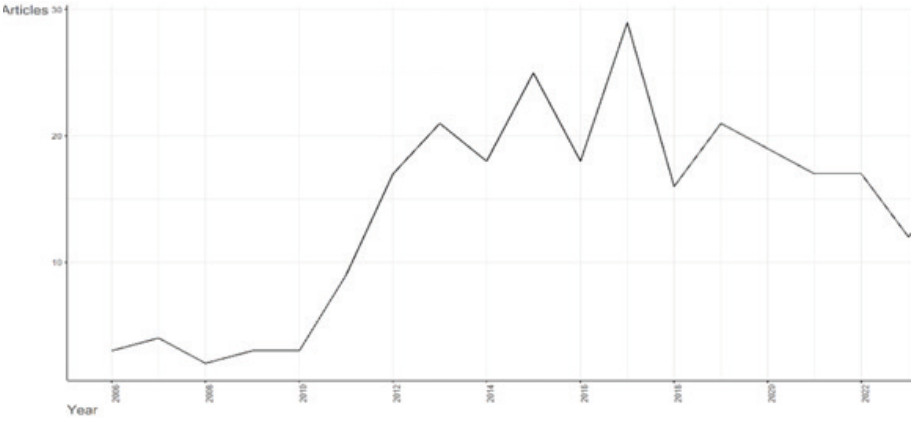
Description	Results
MAIN INFORMATION ABOUT DATA	
Timespan	2006:2024
Sources (Journals, Books, etc)	141
Documents	276
Annual Growth Rate %	2.73
Document Average Age	7.93
Average citations per doc	10.76
References	8394
DOCUMENT CONTENTS	
Keywords Plus (ID)	388
Author's Keywords (DE)	733
AUTHORS	
Authors	566
Authors of single-authored docs	62
AUTHORS COLLABORATION	
Single-authored docs	71
Co-Authors per Doc	2.42
International co-authorships %	36.59
DOCUMENT TYPES	
article	238
article; book chapter	5
article; early access	6
article; proceedings paper	12
proceedings paper	15

Source: Authors

4.1 Dynamics of scientific production

The analysis of the annual number of publications reveals three distinct phases in the development of the literature on fiscal consolidation. The first phase, spanning the period 2006–2010, is characterized by a relatively low and stable number of publications, indicating a marginal research interest prior to the full escalation of the global financial crisis. The second phase, covering the period 2011–2017, exhibits an explosive growth in scientific output. This surge in academic interest is closely associated with the euro area sovereign debt crisis, particularly in Greece, Spain, and Portugal, as well as with the intensification of fiscal reforms following the strengthening of the Stability and Growth Pact. During this period, fiscal consolidation emerged as a core topic of public finance and macroeconomic policy research. The third phase, from 2018 onward, shows a pattern of mild stagnation and occasional decline in publication activity. This trend can be partly explained by the temporary relaxation of fiscal rules during the COVID-19 pandemic and by the redirection of academic attention toward issues such as digital transformation, health economics, and green transition policies.

Figure 2: Annual output of published studies

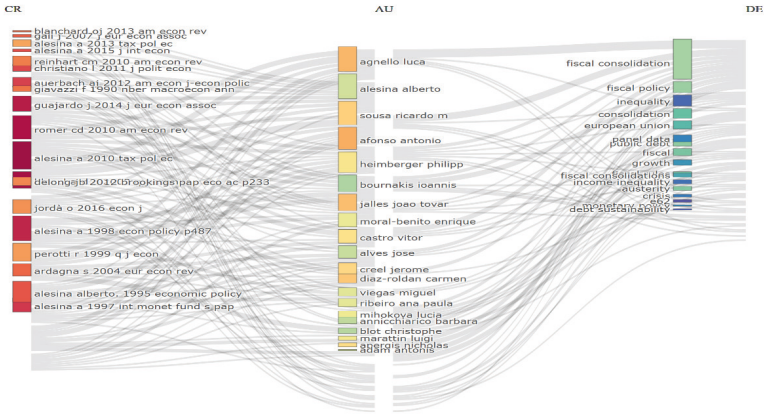


Source: Authors

4.2 Three-field analysis and the structure of the research field

The application of the Three-Field Plot analysis enabled a simultaneous examination of the relationships between the most cited references, the most influential authors, and the dominant research themes. The results indicate strong linkages between seminal works by authors such as Blanchard, Alesina, Reinhart, and Guajardo and the core concepts of fiscal consolidation, fiscal policy, public debt, and economic growth.

Figure 3: Three-field plot



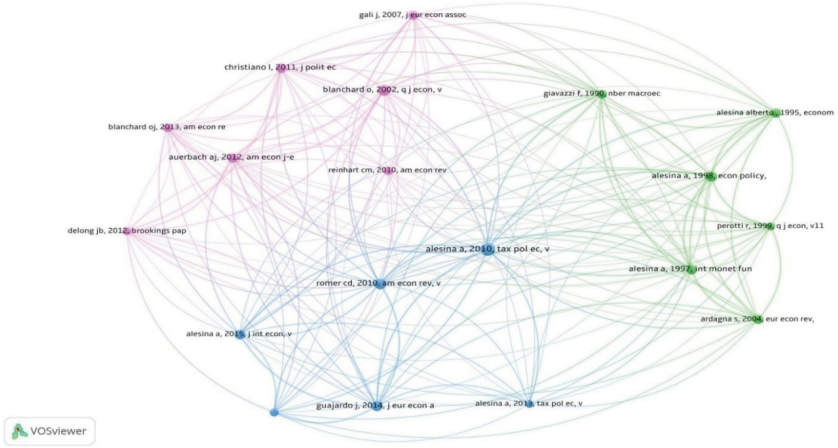
Source: Authors

This structure reflects the existence of several interconnected research streams. On the one hand, a substantial segment of the literature focuses on the macroeconomic effects of fiscal consolidation, while on the other hand, an increasing number of studies examine the institutional and political determinants of fiscal discipline.

4.3 Author co-citation network

The author co-citation network reveals the presence of three dominant clusters. The first cluster includes Alesina, Perotti, Ardagna, and Giavazzi, with a primary focus on theoretical and empirical analyses of fiscal adjustment programs and the composition of consolidation measures. The second cluster is led by Alesina, Guajardo, and Romer, emphasizing empirical databases on fiscal episodes and the estimation of fiscal policy effects. The third cluster groups authors such as Blanchard, Reinhart, Christiano, and DeLong, whose research is oriented toward macroeconomic crises, fiscal multipliers, and long-run fiscal imbalances.

Figure 4: Most-cited authors in the field of fiscal consolidation



Source: Authors

The visualisation highlights three clusters of authors, co-authors, and thematic focal points related to specific aspects of fiscal consolidation:

1. Green Cluster (right side):

- Most-cited authors and co-authors: Alesina, Perotti, Ardagna and Giavazzi.
- Focus: Theoretical and empirical approaches to fiscal consolidation, including research on austerity measures and fiscal adjustment outcomes.

2. Blue Cluster (bottom part):

- Most-cited authors and co-authors: Alesina, Guajardo and Romer.
- Focus: Empirical studies on the effects of fiscal policy, with particular emphasis on datasets related to fiscal consolidation episodes.

3. Purple Cluster (left side):

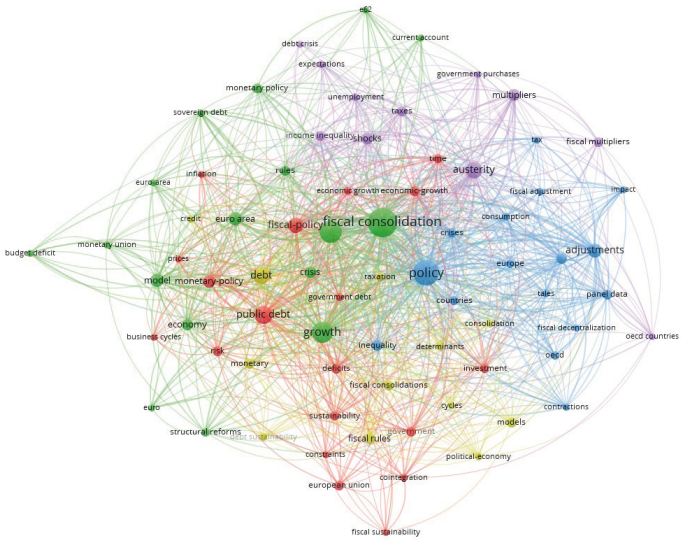
- Most-cited authors and co-authors: Blanchard, Christiano, Reinhart and DeLong.
- Focus: Macroeconomic effects of fiscal policy, including crises, recessions and fiscal multipliers.

The central position of Alberto Alesina within the network highlights his role as an intellectual bridge between theoretical and empirical approaches to fiscal consolidation. The observed cluster structure confirms the multidimensional and methodologically heterogeneous character of this research field.

4.4 Keyword co-occurrence and thematic clusters

The keyword co-occurrence analysis identified four dominant thematic clusters. The first cluster encompasses fiscal governance issues and the interaction between fiscal and monetary policy. The second cluster is oriented toward institutional factors, fiscal decentralization, and the role of subnational governments. The third cluster focuses on long-term public debt sustainability and the political determinants of fiscal constraints. The fourth cluster captures the macroeconomic effects of fiscal consolidation, with a particular emphasis on fiscal multipliers and external imbalances.

Figure 5: Network map of keyword co-occurrence



Source: Authors

The core of the network is formed by terms having a high frequency of occurrence (e.g. fiscal consolidation, policy, debt, growth), confirming their paradigmatic role within the field. However, a more notable finding relates to the heterogeneity of the identified clusters:

1. *Fiscal Governance Framework (green cluster)* encompasses studies addressing the interaction between monetary policy, public finances and cyclical fluctuations.
2. *Institutional Aspects (blue cluster)*, reflected through its key terms, focus on issues of fiscal decentralisation and the role of subnational actors.
3. *Long-Term Sustainability (red cluster)*, characterised by its most frequently used keywords, analyses the links between political determinants, debt dynamics and fiscal constraints.

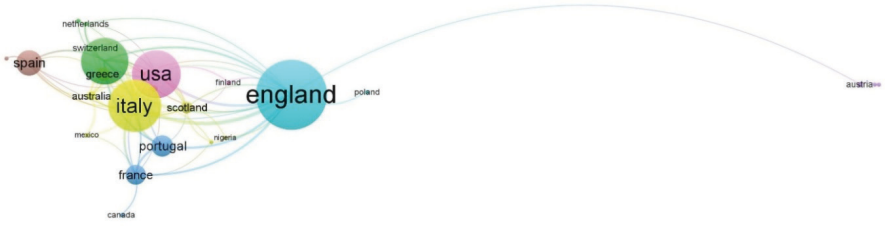
4. *Macroeconomic Effects (purple cluster)* examine the impact of consolidation measures through the lens of fiscal multipliers and external imbalances.

The core of the network is formed by the keywords *fiscal consolidation*, *policy*, *debt*, and *growth*, confirming their paradigmatic status within the contemporary literature.

4.5 International scientific collaboration

The spatial analysis of international scientific collaboration shows a pronounced dominance of European and Anglo-Saxon countries. The United Kingdom, the United States, and Italy occupy central positions within the collaboration network, while Spain, France, Portugal, Greece, the Netherlands, and Switzerland appear as strongly interconnected contributors. China emerges as a more peripheral actor with comparatively weaker links, revealing a clear regional asymmetry in the development of research on fiscal consolidation.

Figure 6: Cross-country author collaboration network

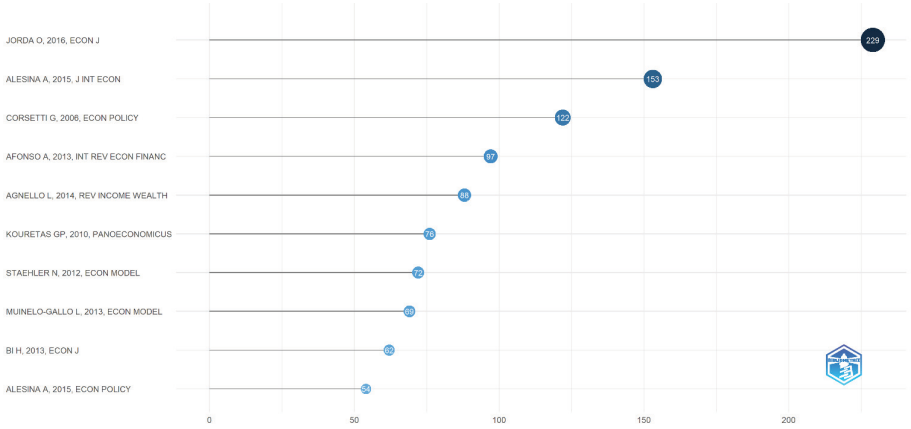


Source: Authors

4.6 Most influential publications

The most highly cited publications confirm the central role of fiscal consolidation in modern macroeconomic debates. Key contributions include the works of Jordà and Taylor (2016), Alesina et al. (2015), and Corsetti and Müller (2006).

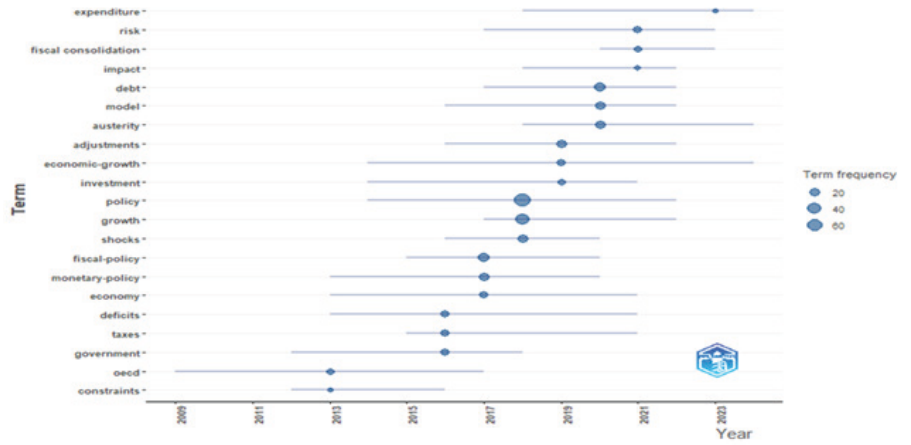
Figure 7: Highly cited articles



Source: Authors

The dominant topics addressed in these studies relate to the impact of fiscal consolidation on economic growth, the interaction between fiscal and monetary policy, the social consequences of fiscal adjustment programs, and the dynamics of public debt markets.

Figure 8: Key Thematic areas in the selected literature



Source: Authors

5 Results and discussion

The results of the bibliometric analysis clearly indicate that fiscal consolidation has evolved into a highly institutionalized and multidimensional research field over the last two decades. The sharp increase in scientific output after 2010 confirms a strong relationship between major macroeconomic crises and the intensification of academic interest in fiscal policy and fiscal adjustment strategies. This finding supports earlier evidence that periods of heightened economic instability tend to generate substantial growth in research activity within the field of public finance.

The identified thematic clusters confirm the multidisciplinary nature of fiscal consolidation research. On the one hand, macroeconomic analyses focusing on output, employment, and growth effects dominate a large part of the literature (Alesina et al., 2015; Guajardo et al., 2014; Blanchard & Leigh, 2013). On the other hand, a growing body of studies emphasizes institutional and political economy dimensions, stressing the importance of fiscal rules, governance quality, and political constraints in shaping the outcomes of consolidation programs (Debrun et al., 2008; Wyplosz, 2012; Bohn, 1998).

The author co-citation network reveals the coexistence of distinct but interconnected research schools. The cluster led by Alesina and his collaborators is primarily associated with the composition-based approach to fiscal consolidation, which differentiates between expenditure-based and revenue-based adjustments and highlights their heterogeneous macroeconomic effects. In contrast, the Blanchard–Reinhart cluster is mainly oriented toward crisis-related dynamics, fiscal multipliers, and debt sustainability under conditions of macroeconomic stress. This intellectual segmentation confirms that no single theoretical framework dominates the interpretation of fiscal consolidation; instead, the field is characterized by methodological pluralism and theoretical competition.

The dominance of European and Anglo-Saxon countries in international collaboration networks reflects the fact that fiscal consolidation has been particularly relevant in advanced economies exposed to sovereign debt pressures, especially within the euro area. However, the limited representation of developing and transition economies suggests a significant geographical research gap, which restricts the external validity of many empirical findings. This observation underscores the necessity of expanding future empirical analyses toward less explored institutional environments, including the Western Balkan region.

The analysis of the most influential publications further confirms that the growth–austerity nexus remains at the core of contemporary scientific debate. While the expenditure-based consolidation hypothesis is supported by several highly cited studies (Alesina & Ardagna, 2010; Afonso & Jalles, 2012), Keynesian-oriented research emphasizes the contractionary short-run effects of fiscal tightening, particularly during recessions (Christiano et al., 2011; Blanchard & Leigh, 2013). The coexistence of these conflicting conclusions reinforces the view that the effects of fiscal consolidation are country-dependent, context-specific, and highly sensitive to policy design.

From a broader perspective, the results suggest that fiscal consolidation should not be interpreted solely as a technical budgetary instrument, but rather as a complex socio-economic process shaped by macroeconomic conditions, institutional frameworks, political incentives, and international constraints. Consequently, the effectiveness of consolidation strategies depends not only on their quantitative magnitude, but also on their qualitative structure, timing, and credibility.

Overall, the findings of this study demonstrate that the academic literature on fiscal consolidation evolves in close interaction with economic crises, fiscal rule reforms, and shifts in macroeconomic paradigms. This dynamic interaction between theory and policy practice further explains the persistent heterogeneity of empirical results and the ongoing debates surrounding the desirability and effectiveness of fiscal consolidation measures.

6 Conclusions

This study provides a comprehensive bibliometric mapping of the scientific literature on fiscal consolidation based on 276 publications indexed in the Web of Science Core Collection over the period 2006–2024. The results confirm that fiscal consolidation has become one of the central research topics in macroeconomics and public finance over the last two decades, closely linked to episodes of economic crises, rising public debt, and major reforms of fiscal frameworks.

The analysis of scientific production dynamics reveals a pronounced cyclical pattern, with a sharp increase in research activity following the global financial crisis and the euro area sovereign debt crisis. These findings suggest that academic interest in fiscal consolidation is largely driven by periods of macroeconomic instability, when fiscal sustainability and budgetary adjustment become urgent policy priorities.

The author co-citation and keyword co-occurrence networks reveal several dominant research clusters, highlighting the multidimensional and heterogeneous nature of fiscal consolidation as a field of study. The prominent position of authors such as Alberto Alesina and Olivier Blanchard reflects not only their high citation impact, but also their foundational role in shaping the main theoretical and empirical debates in the literature. Their work has provided influential interpretations, widely used empirical frameworks, and important reference points for subsequent research on the macroeconomic effects of fiscal adjustment. In this sense, their centrality is not simply a matter of citation frequency, but also a reflection of their lasting influence on key debates concerning the growth effects of fiscal consolidation, the composition of adjustment measures, fiscal multipliers, and debt sustainability. At the same time, the fragmentation of the identified clusters suggests that the literature has developed through the coexistence of competing theoretical approaches and methodological traditions, rather than within a single unified analytical framework.

The thematic evolution of the literature shows a gradual shift of the research focus from short-term stabilization objectives toward institutional, political,

and long-term sustainability issues. While economic growth and public debt remain the core analytical dimensions, increasing attention has been devoted to governance structures, fiscal rules, political economy constraints, and fiscal risk management in recent years. This evolution highlights the growing complexity of fiscal consolidation as a policy process embedded in broader socio-economic and institutional environments. The identified research clusters can be interpreted as bibliometric expressions of broader macroeconomic theories and policy paradigms. More specifically, the cluster associated with Alesina and related authors largely corresponds to the composition-based and partly non-Keynesian view of fiscal consolidation, according to which expenditure-based adjustments may be less contractionary and, under certain conditions, even supportive of growth. In contrast, the Blanchard–Reinhart type cluster is more closely aligned with Keynesian and New Keynesian perspectives, which emphasize fiscal multipliers, demand-side constraints, and the contractionary short-run effects of fiscal tightening, particularly during recessions and periods of macroeconomic stress. At the same time, another part of the literature is linked to institutional and political economy approaches, highlighting the role of fiscal rules, governance quality, and political constraints in determining consolidation outcomes. The coexistence of these clusters confirms that the literature on fiscal consolidation is not organized around a single dominant macroeconomic theory, but rather around several competing and complementary analytical frameworks.

The spatial analysis of international scientific collaboration reveals a strong dominance of European and Anglo-Saxon countries, whereas developing and transition economies remain significantly underrepresented. This geographical imbalance points to an important research gap and limits the generalizability of many existing empirical findings. In this respect, the Western Balkan region represents a particularly relevant and insufficiently explored research area, due to its specific institutional settings, post-transition characteristics, and exposure to repeated fiscal adjustment programs.

The main scientific contribution of this paper lies in the systematic bibliometric mapping of the global research landscape on fiscal consolidation, the identification of key authors, dominant thematic clusters, and international collaboration patterns, as well as in the detection of structural and evolutionary trends within the literature. By providing a structured overview of the intellectual foundations and research directions of the field, the study offers a valuable reference point for future empirical and theoretical investigations.

However, several limitations should be acknowledged. First, the analysis relies exclusively on the Web of Science database, which implies that a part of relevant literature—especially regional studies, policy-oriented reports, and publications in non-English languages—may not be fully captured. Second, bibliometric methods primarily allow for the identification of structural patterns and citation-based influence, but do not provide a deep qualitative assessment of the substantive content of individual studies.

Future research should therefore aim to combine bibliometric techniques with systematic literature reviews and meta-analytical approaches, as well as to expand the data coverage to include multiple citation databases. In addition, further empirical studies should place stronger emphasis on country-

specific and regional analyses of fiscal consolidation, particularly in transition and emerging economies. Such research would contribute to a more comprehensive understanding of how institutional heterogeneity, political constraints, and macroeconomic conditions shape the effectiveness of fiscal consolidation strategies.

Use of Artificial Intelligence (AI) or AI-based Tools: *During the preparation of this manuscript, the author used ChatGPT (OpenAI) as a support tool for translating the manuscript from Serbian into academic English. After using this tool, the author carefully reviewed and edited the content as necessary and takes full responsibility for the content of the published article.*

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Cybersecurity and Operational Risk in Financial Institutions: A PRISMA-Based Bibliometric Review Using NEAR/x Logic

Original scientific paper

Jakub Sopko[1], Leoš Šafár[2]

ABSTRACT

The objective of this study is to systematically review the academic literature on cybersecurity in financial institutions, with a particular emphasis on the area of operational risk and its systemic implications. We apply the PRISMA 2020 framework and employ bibliometric analysis to examine the conceptual and thematic structures in the field. The methodological contribution of the study lies in the application of a semantic proximity logic using the NEAR/15 operator within the Web of Science Core Collection, which enables the identification of relevant publications that explicitly link cybersecurity to operational risk, systemic vulnerability, and regulatory and governance frameworks. After screening and deduplication, a dataset of 613 publications published between 2001 and 2025 was analyzed using the bibliometrix package in R. The findings reveal an exponential increase in research activity after 2015, concentrated in journals such as IEEE Access, Computers & Security, and the Journal of Cybersecurity, and spanning 75 countries led by the United States, India, and China. Citation and co-citation analyses indicate that the intellectual base of the field is anchored in cyber insurance, information security investment, and the economic costs of breaches, highlighting the multidisciplinary nature of the discourse. The results show that literature remains fragmented across disciplinary and regulatory domains, underscoring the need for integrated frameworks that treat cybersecurity simultaneously as an operational and a systemic risk. The study concludes that strengthening the resilience of the financial system requires conceptual, regulatory, and governance approaches that better reflect the cross-border and networked character of cyber threats.

***Keywords**: Cybersecurity, Cyber risk, Operational risk, Banks, Bibliometric analysis*

1 *Assistant Professor, Technical University of Košice, Faculty of Economics, Němcovej 32, 040 01 Košice, Slovakia. ORCID: https://orcid.org/0000-0002-7314-828X. +421 55 602 3277. E-mail: jakub.sopko@tuke.sk.*

2 *Assistant Professor, Technical University of Košice, Faculty of Economics, Němcovej 32, 040 01 Košice, Slovakia. ORCID: https://orcid.org/0000-0001-8466-0644. +421 55 602 3277. E-mail: leos.safar@tuke.sk.*

***JEL classification**: G2, G32, K24, L14, M15*

1 Introduction

The rapid digitalization of the global financial sector has become an issue of great importance recently due to fundamental changes in the structure of financial institutions, communication, and risk management. In just the past few years, this sector has emerged as a phenomenon of exceptional interest for more vulnerable to sophisticated cyberattacks. Cyberattacks on central banks and payment systems in recent years have highlighted their potential to cause serious damage and losses to institutions and the overall economy (Aldasoro et al., 2020; Bouveret, 2018).

The Basel Committee on Banking Supervision (BCBS) classifies cyber events under the category of "business disruption and system failures," thus embedding them into the existing operational risk taxonomy (Peihani, 2022). Recent evidence suggests that this categorization may insufficiently capture the systemic nature of cyber threats, which often transcend institutional boundaries and spread through financial networks in complex ways (Aldasoro et al., 2020; Peihani, 2022). Cyber incidents may represent a dual challenge: on the one hand, they affect the confidentiality, availability, and integrity of information systems; on the other hand, they carry the potential to amplify system-wide financial fragility through loss of trust and operational paralysis (Bouveret, 2018; Uddin et al., 2020). Aldasoro et al. (2020) document that value-at-risk from cyber losses can represent up to one-third of all operational value-at-risk for banks, despite the relatively lower frequency of cyber events compared to traditional operational failures (Uddin et al., 2020).

A growing body of research also highlights the critical role of cybersecurity governance in mitigating these risks. Financial institutions are increasingly adopting structured frameworks such as NIST, ISO/IEC 27001, COBIT, and FAIR to manage cyber threats, to align technical measures with business objectives, and to quantify risk in financial terms (Türegün, 2025). However, there is no global consensus on how cyber resilience should be measured or integrated into supervisory regimes. The literature suggests that a move beyond technical cybersecurity, toward broader cyber resilience and adaptive governance, is essential to address emerging threats and sector interdependencies (Campoverde-Molina & Luján-Mora, 2025; Peihani, 2022; Uddin et al., 2020).

There is limited consensus on how cyber resilience should be defined or measured. While the literature increasingly addresses technical and institutional aspects of cyber risk, relatively few studies have developed comprehensive conceptual frameworks that connect cybersecurity to both operational vulnerability and broader financial system stability (Uddin et al., 2020).

Our aim is to fill these gaps by a systematic bibliometric analysis of the literature on cyber-security risk and vulnerabilities in the financial system, with a focus on financial institutions such as banks, insurers and fintech companies. The study draws on a proximity-based search technique, using NEAR/15 as a reference

for obtaining and evaluating conceptual proximity between cybersecurity and key topics such as operational risk, financial stability, regulatory frameworks and governance. By comparing the thematic structure and the volume of the literature collected under the NEAR parameter, this paper provides both a sectoral summary and a methodological insight into how the search logic shapes academic discovery.

2 Literature review

The vulnerability of the contemporary financial landscape to malicious cyber-activity stems from a volatile mix of massive asset concentration, global systemic interconnectedness, and an aggressive, ongoing digital transformation. As primary custodians of immense volumes of sensitive data, financial institutions provide a high-value target for identity theft and fraud (Leuprecht, 2019; Natalucci et al., 2024; Vedral, 2021).

2.1 Cybersecurity in financial institutions

In recent years, we can see that the financial sector is dependent on IT and digital technologies and is increasingly vulnerable to cyber threats (Financial Stability Board, 2020; Kopp et al., 2017). Technological innovation is generally intended to increase operational efficiency and competitiveness, but this may also lead to new vulnerabilities, as technology becomes more complex.

The relationship between IT investments and bank performance is the subject addressed in the literature. On the one hand, studies show that adopting technologies can lead to increased efficiency and improved customer service (Gutu, 2014; Lee & Mithas, 2014), but on the other hand, some authors have warned that such adoption, without parallel integration of cyber security, may exacerbate the exposure to operational risks (Beccalli, 2007; Ho & Mallick, 2010). The paradox is that digital transformation increases the accessibility of services but may also increase vulnerability to cyberattacks (Longstaff et al., 2020). Empirical evidence suggests that banks are vulnerable not only to direct financial losses due to cyber incidents, but also to wider second-order effects such as erosion of reputational integrity, regulatory scrutiny and a decline in investor confidence. Beccalli (2007) emphasizes that even large-scale IT investments do not guarantee improved financial outcomes and may generate negative returns if cyber resilience is not concurrently addressed. Khoury and Rolland (2006) argue that systemic IT interdependencies in financial networks can result in a domino effect, where the compromise of one institution may trigger instability across the broader system. Cherdantseva et al. (2016) and Ralston (2007) underline that technical tools for detecting and measuring cyber risks often fail to capture the underlying vulnerabilities in banking systems. Gracie (2015) and Brown (2015) highlight the difficulty of accurately assessing cyber exposures due to limited historical data, rapidly evolving threat vectors and the absence of harmonized standards for disclosure. These challenges complicate not only the readiness of firms but also macro-prudential supervision. Willison and Warkentin (2013) argue that social engineering and insider threats are key to breaches and should be incorporated into risk management models.

2.2 Cyber risk as operational risk

The classification of cyber risk as a subset of operational risk is widely recognized. According to the Basel Committee on Banking Supervision (2021), operational risk is defined as "the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events." Under this taxonomy, cyber incidents are usually classified as "business disruptions and system failures," and fall under the broader umbrella of operational losses (Aldasoro et al., 2020).

Recent literature shows that this integration has been extensively investigated. Bouveret (2018) and Peihani (2022) argue that cyber risk has different characteristics that distinguish it from traditional forms of operational risk. Bouveret (2018) estimates that a large-scale cyberattack could result in losses equivalent to 0.5 percent of GDP in advanced economies. Adelmann et al. (2020) emphasize that cyber events affecting core financial market infrastructures could have systemic effects. These findings suggest that cyber risk must be addressed through macroprudential lenses, not solely as a firm-level operational risk.

The modeling and quantification of cyber risk present further methodological challenges. As stated by Aldasoro et al. (2020) and Ryman-Tubb et al. (2018), cyber incidents are often underreported and inconsistently classified. This has motivated the development of alternative tools, including scenario-based stress testing, network contagion models, and cyber insurance-based pricing mechanisms (Eling & Wirfs, 2016).

2.3 Cybersecurity and systemic financial vulnerability

Cyber threats are no longer limited to individual institutions but increasingly pose a systemic threat to financial system stability (Peihani, 2022; Adelmann et al., 2020). The macro-prudential consequences of cyber risk have become a central issue in the debate on financial stability. Adelmann et al. (2020) stressed that cyber incidents targeting the core financial institutions or infrastructures could disrupt the functioning of markets, disrupt liquidity flows and reduce confidence in system-critical intermediaries. Similarly, the US Office of Financial Research (2017) warned that erosion of public trust, even in the wake of a single cyber incident, could lead to wider instability. Kopp et al. (2017) identify that cyber events may spread through shared infrastructure, correlated exposures, and vendor interdependencies. These transmission mechanisms resemble liquidity shocks observed in traditional financial contagion models; however, they differ in that cyber shocks are frequently non-linear, asynchronous, and difficult to trace (Aldasoro et al., 2020; Bouveret, 2018). Systemic vulnerability is further compounded by the high concentration of service dependencies among financial institutions. A disruption may simultaneously affect numerous institutions, even when their internal cyber defenses are strong (Aldasoro et al., 2020; Kopp et al., 2017). Another critical barrier to systemic cyber risk management is the lack of consistent incident reporting and data sharing. As noted by Bouveret (2018), cyber incidents are underreported, and there is considerable heterogeneity

in the classification and disclosure standards applied across jurisdictions. We believe that this limits the ability of financial authorities to construct aggregate exposure metrics and that it undermines efforts to model cross-institutional vulnerabilities. Moreover, traditional stress-testing frameworks were not designed to simulate the behavioral and operational complexity of cyber incidents and therefore provide limited insight into systemic contagion scenarios.

2.4 Governance, regulation and risk taxonomies

Regulatory frameworks have generally recognized cyber risk as part of operational risk, based on definitions established under Basel II and related supervisory standards (Basel Committee on Banking Supervision, 2021; Uddin et al., 2020). However, this classification is increasingly viewed as insufficient to address the scale of modern cyber threats. Regulatory initiatives in both the United States and the European Union have attempted to respond to this gap. In the EU, the proposed Digital Operational Resilience Act (DORA) introduces a harmonized framework that mandates incident reporting, risk management of third-party ICT providers, and the testing of digital operational resilience (Financial Stability Board, 2020; Wolff & Lehr, 2018). Similarly, in the United States, legislation such as the Cybersecurity Information Sharing Act (CISA) and supervisory guidance from the Federal Financial Institutions Examination Council (FFIEC) aim to improve sector-wide preparedness and reporting (Wolff and Lehr, 2017).

Recent literature has focused on the need for clearly defined taxonomies of cyber risk that go beyond broad event categories. Cebula and Young (2010) organize cyber incidents by threat source, method, and affected systems. This approach helps financial institutions understand which threats are most relevant for specific operational contexts and which mitigation tools are appropriate (Bouveret, 2018). Gatzert and Schubert (2022) identify that financial institutions with formal cybersecurity governance structures, are better equipped to mitigate losses and coordinate incident response. Héroux and Fortin (2022) found that disclosure practices and board awareness are positively correlated with resilience during cyber incidents. Regulatory authorities in several jurisdictions now require boards to play an active role in supervising cyber preparedness, reviewing test results, and evaluating third-party ICT risk (Financial Stability Board, 2020).

The Financial Stability Board has outlined the principles for cyber incident response and recovery (Financial Stability Board, 2020). These efforts align with the recommendations by Groenendaal and Helsloot (2021), who highlight the value of collective sense-making and coordination in crisis governance. Similarly, Kashyap and Wetherilt (2019) propose a resilience-oriented framework and Hartmann and Carmenate (2021) propose structured cybersecurity governance committees to streamline decision-making during high-pressure situations. Regulatory fragmentation across jurisdictions and lack of harmonized reporting standards continue to inhibit effective cyber governance.

3 Methodology and empirical data

In this section, the methods used in this work are explained in detail. We apply bibliometric and text mining analyses to assess the intellectual structure of research on cyber risk in the financial sector. We follow the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework (Page et al., 2021). The PRISMA protocol guided the identification, screening, eligibility, and inclusion stages of our review, allowing us to minimize potential selection bias and to ensure that only relevant, high-quality publications were retained for analysis.

The study is guided by the following research questions:

> **RQ1**. What are the leading and most influential papers in terms of popularity and prestige in the field of cybersecurity in the financial sector?
>
> **RQ2**. What are the existing clusters of current research within cybersecurity in the financial sector?

We began the review process by constructing four conceptually distinct but interrelated search strategies, each corresponding to a major research theme: (S1) cybersecurity in financial institutions, (S2) cyber risk as operational risk, (S3) cybersecurity and systemic financial vulnerability, and (S4) governance, regulation, and risk taxonomies. All searches were conducted within the Web of Science Core Collection using the NEAR/15 proximity operator. This design enabled us to retrieve documents in which cyber-related terms appeared within fifteen words of financial, operational, or regulatory expressions, ensuring contextual relevance and reducing the inclusion of irrelevant records.

Table 1: PRISMA approach for systematic literature review

Study design	This study presents a literature review that systematically synthesizes existing research using a clearly defined, transparent, and methodologically rigorous procedure.
Review protocol	To reduce the risk of “biased post hoc decisions in review methods” (Liberati et al., 2009), the search criteria and corresponding keywords were defined in advance.
Eligibility criteria	The review considered only peer-reviewed journal articles, conference proceedings, reviews, and book chapters. Relevant studies were retrieved from the Web of Science database using author-developed search queries. The resulting bibliometric data were subsequently analyzed through mapping and clustering techniques.
Search timeframe	2000 – August 2025
Document types	Journal articles, conference proceedings, reviews, book chapters
Language	English

Fields	Topic search (TS) = Title, Abstract, Keyword Plus, Author Keywords.
Thematic area	**Sample Keywords**
Search 1 (S1) Cybersecurity in financial institutions	(("bank*" OR "banking institution*" OR "financial institution*" OR "financial sector" OR "financial industry" OR "financial market*" OR "pension fund*" OR "insurance compan*" OR "insurer*" OR "commercial bank*" OR "central bank*" OR "fintech" OR "financial service*" OR "capital market*" OR "asset manager*" OR "investment firm*") NEAR/15 ("cybersecurity" OR "cyber security" OR "cyber-security" OR "cyber risk*" OR "cyber threat*" OR "cyber attack*" OR "cyber-attack*" OR "cyber incident*" OR "cyber harm*" OR "cybercrime" OR "data breach*" OR "data leakage" OR "information security" OR "information systems secur*" OR "IT secur*" OR "digital secur*" OR "network secur*" OR "computer secur*" OR "cyber resilience"))
Search 2 (S2) Cyber risk as operational risk	S1 AND (("operational risk*" OR "non-financial risk*" OR "enterprise risk management" OR "risk control*" OR "risk management" OR "risk assessment*" OR "risk monitoring" OR "risk mitigation" OR "risk response" OR "risk management framework*" OR "operational cost*" OR "operational framework*" OR "operational expenditure*" OR "operational spend*" OR "operational resilience" OR "business continuity" OR "ICT risk management" OR "operational disruption" OR "operational outage" OR "IT risk management") NEAR/15 (Cyber terms))
Search 3 (S3) Cybersecurity and systemic financial vulnerability	S1 AND (("systemic risk*" OR "system-wide risk*" OR "financial stability" OR "financial contagion" OR "bank* vulnerability" OR "macroprudential risk*" OR "interconnectedness" OR "risk propagation" OR "cyber contagion" OR "spillover*" OR "domino effect" OR "third-party risk" OR "supply chain risk") NEAR/15 (Cyber terms))
Search 4 (S4) Governance, regulation and risk taxonomies	S1 AND (("regulation" OR "governance" OR "supervision" OR "taxonomy" OR "regulatory framework*" OR "DORA" OR "NIS Directive" OR "NIS 2 Directive" OR "ENISA" OR "NIST Cybersecurity Framework" OR "NIST CSF" OR "compliance" OR "risk disclosure" OR "board oversight" OR "regulatory compliance" OR "cybersecurity governance" OR "digital governance" OR "supervisory framework*" OR "risk oversight" OR "cybersecurity compliance" OR "risk classification*" OR "BCBS" OR "FSB" OR "EBA" OR "FED" OR "ECB") NEAR/15 (Cyber terms))

Source: Authors

For four thematic areas we applied the textual search:

1. TS (Topic Search)= S1 (Search 1: Financial actors NEAR/15 Cyber terms3)
2. TS = S1 AND S2 (Search 2: Operational risk terms NEAR/15 Cyber terms)
3. TS = S1 AND S3 (Search 3: Systemic financial vulnerabilities terms NEAR/15 Cyber terms)
4. TS = S1 AND S4 (Search 4: Regulation framework and governance terms NEAR/15 Cyber terms).

The initial search yielded 1,060 records in total: 843 from S1, 107 from S2, 13 from S3, and 97 from S4 (Table 2). Following the PRISMA protocol, we applied several sequential filters (Figure 1). In the identification stage, we removed document types that did not constitute original research, including editorials, corrections, meeting abstracts, and early-access materials. During screening, we further excluded studies outside the business, economics, and finance domains, as well as those written in languages other than English. The eligibility stage focused on retaining peer-reviewed journal articles, conference proceedings, reviews, and book chapters that explicitly addressed cybersecurity, operational risk, or related governance topics within financial contexts.

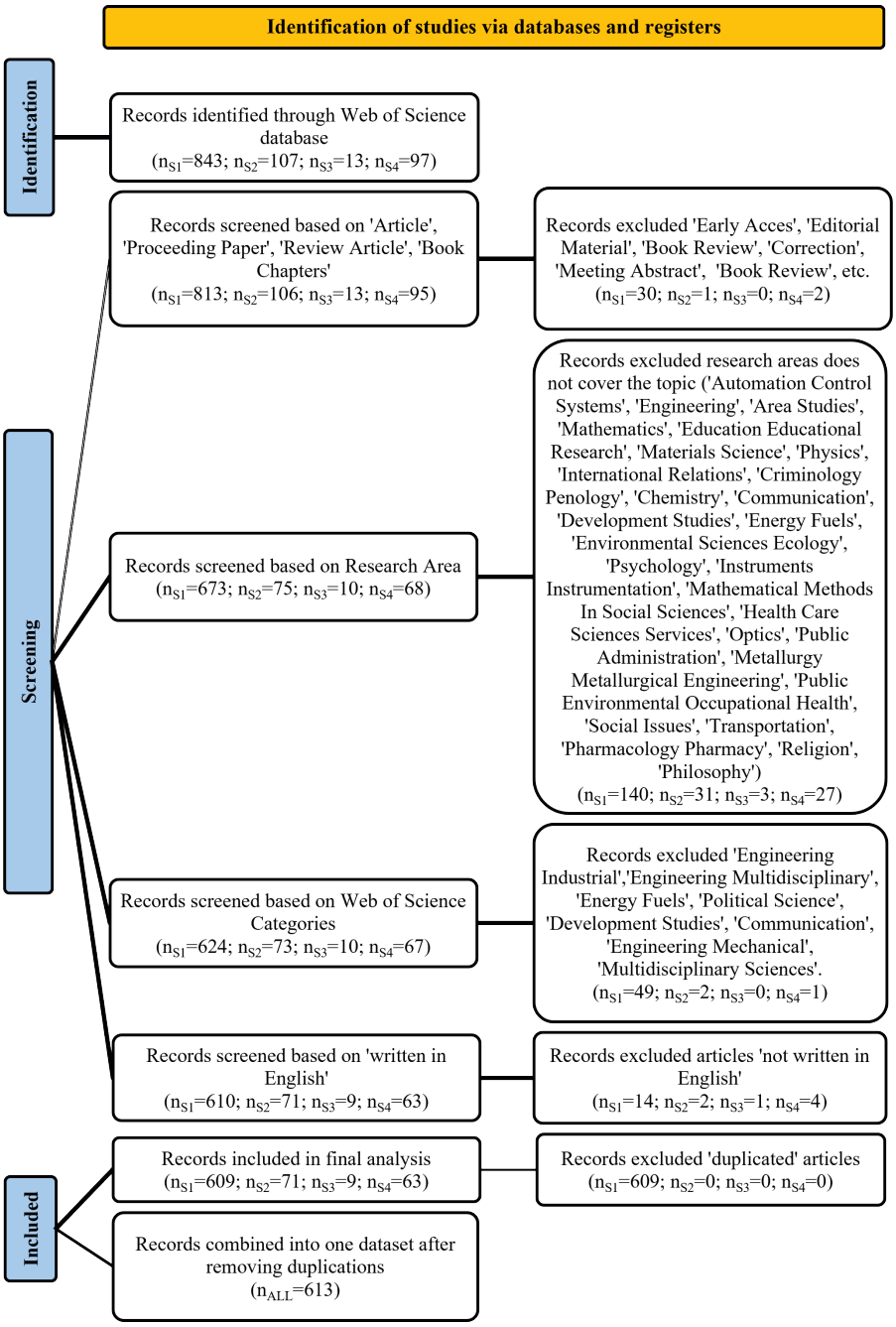
Table 2: Process stages

INITIAL SEARCH			
S1	S2	S3	S4
843	107	13	97
APPLYING PRISMA GUIDELINES			
S1	S2	S3	S4
610	71	9	63
REMOVING DUPLICATIONS			
S1	S2	S3	S4
609	70	9	63
COMBINING ALL SEARCHES INTO ONE DATASET AFTER REMOVING DUPLICATIONS			
ALL~(S1+S2+S3+S4)			
613			

Source: Authors

3 *Cyber terms are represented by the keyword vector: ("cybersecurity" OR "cyber security" OR "cyber-security" OR "cyber risk*" OR "cyber threat*" OR "cyber attack*" OR "cyber-attack*" OR "cyber incident*" OR "cyber harm*" OR "cybercrime" OR "data breach*" OR "data leakage" OR "information security" OR "information systems secur*" OR "IT secur*" OR "digital secur*" OR "network secur*" OR "computer secur*" OR "cyber resilience").*

Figure 1: PRISMA flowchart and applied sequential filters



Source: Authors according to Page et al., 2021

After completing these stages, 753 documents met our inclusion criteria. We then examined the four subsets for duplication, as some articles appeared under multiple thematic searches. Using the duplicatedMatching() function in the bibliometrix package in R, we systematically removed overlapping entries, resulting in a consolidated dataset of 613 unique publications.

We present the structure and the main descriptive characteristics of our final dataset in Table 3. The documents are distributed across 453 distinct sources without publication in 2000, reflecting the field's broad and still-diffuse disciplinary orientation. A total of 1,811 authors contributed to the corpus, underscoring the collaborative nature of cybersecurity research in finance, while single-authored works represent only a small fraction. Journal articles (353) and conference papers (231) dominate the dataset, complemented by a few reviews and book chapters, which together indicate both empirical and conceptual engagement with the topic. The average citation rate of 11.61 per document suggests a growing academic interest and steady integration of cybersecurity into financial research.

Table 3: The structure of the final dataset

Documents	613
Period	2001-2025
Sources (Journals, Books, etc.)	453
Keywords Plus (ID)	638
Author's Keywords (DE)	2065
Average citations per doc	11.61
Authors	1811
Article	353
Article; Book Chapter	7
Article; Proceedings Paper	4
Proceedings Paper	231
Review	18
Authors of single-authored docs	87
Single-authored docs	92

Source: Authors

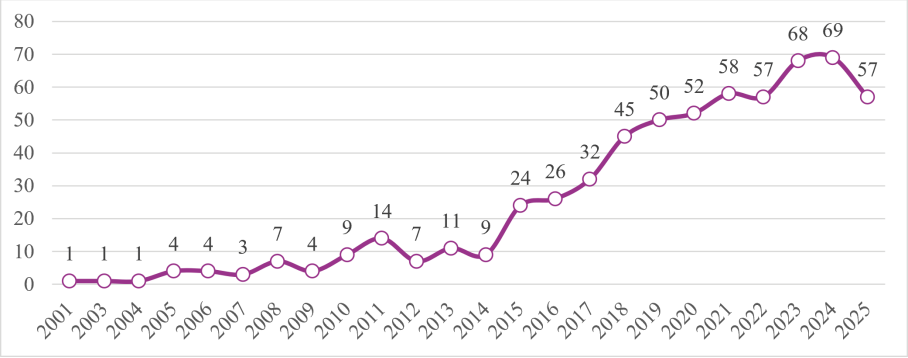
The bibliometric analysis was conducted via the R package bibliometrix, which offers comprehensive tools for scientific mapping and content analysis of bibliographic data (Aria and Cuccurullo, 2017).

4 Results and discussion

Figure 2 illustrates the temporal evolution of publications on cybersecurity and operational risk in financial institutions between 2001 and August 2025.

A pronounced surge is evident from 2016 onward, coinciding with heightened regulatory attention to digital resilience and the integration of cybersecurity into financial stability frameworks.

Figure 2: Number of articles published between 2001 and August 2025



Source: Authors

4.1 Descriptive data analysis

In total, studies originate from 75 countries, a figure that underlines the topic's global relevance. Even so, the landscape remains concentrated: 20 countries are represented by a single publication, and roughly 50 have produced no more than five. This bias indicates that most activity is embedded in a limited set of research economies. The United States contributes the largest share with 93 articles (see Table 4), followed by India (66) and China (38), together forming the core of the publication network. Several other countries—particularly the United Kingdom, Australia, and Malaysia—also appear as important nodes, often through multi-institutional collaborations. When international partnerships are considered, considerable variation emerges. Malaysia's MCP ratio of 0.57 and Korea's 0.41 contrast sharply with the more domestically focused patterns observed in Russia (0.06) and India (0.09). What becomes apparent is that, although cybersecurity and financial stability are matters of worldwide concern, active transnational collaboration is largely confined to a handful of regions.

Table 4: The most productive countries based on the corresponding author affiliation

Country	Articles	Freq	SCP	MCP	MCP_Ratio
USA	93	0.1527	76	17	0.1828
INDIA	66	0.1084	60	6	0.0909
CHINA	39	0.064	34	5	0.1282

UNITED KINGDOM	33	0.0542	20	13	0.3939
AUSTRALIA	21	0.0345	16	5	0.2381
MALAYSIA	21	0.0345	9	12	0.5714
SOUTH AFRICA	20	0.0328	20	0	0
KOREA	17	0.0279	10	7	0.4118
RUSSIA	17	0.0279	16	1	0.0588
CANADA	16	0.0263	11	5	0.3125

Source: Authors

Table 5 presents the distribution of articles across journals that have published at least five studies on cybersecurity and operational risk in financial institutions. Although the full dataset encompasses 453 distinct sources, most of them contribute only minimally to the field. In numerical terms, 389 journals include a single article, while 37 contain two, and only 10 more than five. We can say that research activity is highly dispersed, yet meaningful topics are concentrated within a relatively small group of specialized journals. Among these, IEEE Access and Computers & Security clearly dominate, together accounting for 36 papers and more than 980 citations. Their prominence is hardly surprising, given their consistent focus on applied cybersecurity and information assurance. The Journal of Cybersecurity, Risks, and the Geneva Papers on Risk and Insurance - Issues and Practice, adds a complementary lens, linking technological security with insurance, governance, and risk management perspectives. Interestingly, several of these leading journals, hold a Journal Impact Factor and are listed as current content sources, which strengthens their role as principal publication venues.

Table 5: Distribution of articles across journals with basic metrics (journals with 5 and more articles)

Element	TC	NP	H	G	M	PY	JIF	CC
IEEE ACCESS	392	19	11	19	1.83	2020	3.6	Yes
COMPUTERS \& SECURITY	591	17	11	17	0.44	2001	5.4	Yes
JOURNAL OF CYBERSECURITY	180	9	5	9	0.63	2018	3.2	No
RISKS	48	9	4	6	0.67	2020	1.5	No
GENEVA PAPERS ON RISK AND INSURANCE-ISSUES AND PRACTICE	111	8	6	8	0.75	2018	3.3	Yes
INFORMATION AND COMPUTER SECURITY	76	8	5	8	0.45	2015	1.8	No

INTERNATIONAL JOURNAL OF SECURITY AND ITS APPLICATIONS	21	7	3	4	0.21	2012	-	-
FINANCIAL AND CREDIT ACTIVITY-PROBLEMS OF THEORY AND PRACTICE	6	6	2	2	0.40	2021	0.7	No
JOURNAL OF OPERATIONAL RISK	22	6	3	4	0.27	2015	0.8	Yes
INTERNATIONAL JOURNAL OF ADVANCED COMPUTER SCIENCE AND APPLICATIONS	16	5	2	4	0.13	2011	0.9	No

*TC – Total Citations; NP – Number of Publications; H – h-index; G – g-index; M – m-index; PY – Publication Year Start; JIF – Journal Impact Factor; CC – Current Content
Source: Authors

We consider in our descriptive analysis the citation-based indicators such as the h-index, g-index, and m-index (Table 5). The h-index, often used as a measure of combined productivity and impact, identifies the number of papers within a journal that have each been cited at least the same number of times. By contrast, the g-index places greater weight on highly cited papers; it is defined as the largest number g for which the top g publications collectively have at least g^2 citations. To account for differences in journal longevity, the m-index adjusts the h-index by dividing it by the number of years since the first publication of the journal, thereby allowing a fairer comparison between established and emerging outlets. These indicators may contribute to a more reliable understanding of literature influence, highlighting not only the consistency of journal performance but also the degree to which individual publications shape ongoing debates within cybersecurity and financial risk research.

Table 6: The most productive authors

Authors	Articles	Total citations	Authors Fractionalized	Articles Fractionalized
FRANKE U	7	107	FRANKE U	3.33
NIYATO D	6	23	IFINEDO P	3
LEE J	5	123	MOECKEL C	2.5
MUKHOPADHYAY A	5	157	KAO DY	2
PAL R	5	96	ORLANDO A	2

WANG P	5	22	RADA IC	2
ELING M	4	45	TROMMLER P	2
FEDOTOVA GV	4	4	DHILLON G	1.83
LIU M	4	78	MUKHOPADHYAY A	1.73
RADA IC	4	12	ELING M	1.67

Source: Authors

Table 6 provides insight into the authorship structure of the dataset, which, as mentioned above, includes the contributions of 1,811 authors. The left section of Table 6 shows the most productive authors by total number of publications and citations, while the right section modifies this ranking by using fractionated citations. Fractionalized articles represent the share of contributions in co-authored papers. The examination of both perspectives provides a more balanced picture of the dynamics in research productivity and cooperation. In terms of total outputs, Franke U. is the most prominent contributor, with seven publications and 107 citations, followed by Mukhopadhyay A., with five papers and 157 citations, which suggests a significant impact despite the smaller number of publications. Repeated names on both sides of the table also indicate a relatively small group of researchers who have been central to the discussion on cyber risk and financial resilience.

Table 7 shows 17 articles cited 10 times per year or more, representing the most influential articles in our sample. Table 7 summarizes the most frequently cited papers in the dataset and highlights studies that have consistently contributed to the understanding of cyber security and financial risk. The article by Rajapathirana and Hui (2018) on innovation and company performance and the study by Siyal et al (2019) on the use of the blockchain in finance are particularly cited and show their central role in linking digital transformation to company performance.

Table 7: The most cited articles

Authors & Year	**Title**	**TC**	**TCpY**	**Source**
Rajapathirana and Hui (2018)	Relationship Between Innovation Capability, Innovation Type, And Firm Performance	470	58.8	Journal of Innovation & Knowledge
Siyal et al. (2019)	Applications Of Blockchain Technology in Medicine and Healthcare: Challenges and Future Perspectives	213	30.4	Cryptography

Authors & Year	Title	TC	TCpY	Source
Mhlanga (2020)	Industry 4.0 In Finance: The Impact of Artificial Intelligence (Ai) On Digital Financial Inclusion	166	27.7	International Journal of Financial Studies
Zhang et al. (2022)	Explainable Artificial Intelligence Applications in Cyber Security: State-Of-The-Art in Research	108	27.0	IEEE Access
Amir et al. (2018)	Do Firms Underreport Information on Cyber-Attacks? Evidence From Capital Markets	139	17.4	Review of Accounting Studies
Kunreuther and Heal (2003)	Interdependent Security	376	16.3	Journal of Risk and Uncertainty
Injadat et al. (2021)	Machine Learning Towards Intelligent Systems: Applications, Challenges, And Opportunities	81	16.2	Artificial Intelligence Review
Rodrigues et al. (2022)	Artificial Intelligence, Digital Transformation and Cybersecurity in The Banking Sector: A Multi-Stakeholder Cognition-Driven Framework	61	15.3	Research in International Business and Finance
Aldasoro et al. (2022)	The Drivers of Cyber Risk	55	13.8	Journal of Financial Stability
Romanosky et al. (2019)	Content Analysis of Cyber Insurance Policies: How Do Carriers Price Cyber Risk?	95	13.6	Journal of Cybersecurity
Huang and Wang (2021)	Do Banks Price Firms' Data Breaches?	58	11.6	The Accounting Review
AL-Dosari et al. (2024)	Artificial Intelligence and Cyber Defense System for Banking Industry: A Qualitative Study of Ai Applications and Challenges	23	11.5	Cybernetics and Systems

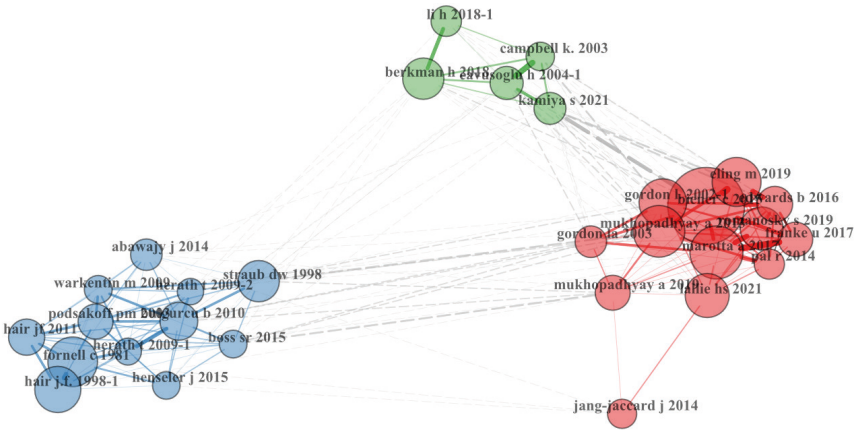
Authors & Year	Title	TC	TCpY	Source
Noor et al. (2019)	A Machine Learning-Based Fintech Cyber Threat Attribution Framework Using High-Level Indicators of Compromise	80	11.4	Future Generation Computer Systems
Tam and Jones (2019)	Macra: A Model-Based Framework for Maritime Cyber-Risk Assessment	77	11.0	WMU Journal of Maritime Affairs
Chakraborty et al. (2016)	Online Shopping Intention in the Context of Data Breach in Online Retail Stores: An Examination of Older and Younger Adults	102	10.2	Decision Support Systems
Salovaara et al. (2019)	High Reliability in Digital Organizing: Mindlessness, The Frame Problem, And Digital Operations	71	10.1	MIS Quarterly
Armenia et al. (2021)	A Dynamic Simulation Approach to Support the Evaluation of Cyber Risks and Security Investments in SMEs	50	10.0	Decision Support Systems

Source: Authors

4.2 Content analysis

We summarize the most influential references in Table 8. Combined with the results of the Figure 3, which represents the Co-citation network, we can explain the links between the most influential references. We can see three clusters: the red cluster lies at the heart of the cyber-financial literature and includes some of the most highly cited papers on cyber risk (Gordon & Loeb, 2002; Gordon et al. 2003; Marotta et al. 2003), as well as more recent contributions that have established the actuarial foundations for the quantification and the insurability of cyber risks (Biener et al. 2015; Eling & Wirfs, 2019), which have laid the foundations for the economics logic and actuarial modelling of cyber security. The red cluster also includes the methodological work of Romanosky et al. (2019), who provide a comprehensive framework to link technical incidents to financial exposures and Mukhopadhyay et al. (2013) that expand the understanding of cyber risk pricing by proposing models to help firms decide on the utility of cyber-insurance products.

Figure 3: Co-citation Network



Source: Authors

The second cluster (green) includes studies such as those by Cavusoglu et al. (2004), Campbell et al. (2003), Kamiya et al. (2021), and Berkman et al. (2018). These papers converge on the idea that cyber incidents produce measurable economic signals: declines in stock prices, increased volatility, and loss of credibility. These works represent the applied dimension of cyber risk research, bringing theoretical models from Cluster 1 to bear on the real world evidence of the impact of cyber risk on markets and on institutional responses.

Table 8: The most influential resource references

Cited references	Citations	Cited references	Citations
Biener et al. (2015)	32	Böhme and Schwartz (2010)	12
Marotta et al. (2017)	24	Bulgurcu et al. (2010)	12
Gordon and Loeb (2002)	19	Campbell et al. (2003)	12
Fornell and Larcker (1981)	16	Lallie et al. (2021)	12
Franke (2017)	16	Straub and Welke (1998)	12
Eling and Wirfs (2019)	15	Berkman et al. (2018)	11
Gordon et al. (2003)	15	Eling and Schnell (2016)	11
Mukhopadhyay et al. (2013)	15	Khalili et al. (2018)	11
Romanosky et al. (2019)	15	Lelarge and Bolot (2009)	11

Edwards et al. (2016)	14	Herath and Rao (2009)	10
Hair (1998)	14	Romanosky et al. (2016)	10
Cavusoglu et al. (2004)	13	Woods et al. (2017)	10
Kamiya et al. (2021)	13	Woods and Simpson (2017)	10
Pal et al. (2014)	13		

Source: Authors

The blue cluster aggregates methodological pillars and conceptual frameworks that are applicable throughout the field, including works such as Fornell (1981), Hair et al. (1998), Podsakoff et al. (2003), and Straub (1998). Even though these works are not directly aligned with cybersecurity, they form the basis for measurement validity, model estimation, and behavioral interpretation within the other clusters.

The most significant subjects covered in an article from the author's perspective are represented by the author's keywords (left side of Table 9). The keywords-plus (right side of Table 9) are defined indirectly and reveal the primary intellectual foundations that form the author's background because they are automatically generated from the names of the sources that the author of the article cites.

Table 9: Keyword occurrence analysis

Author Keywords (DE)	**Articles**	**Keywords-Plus (ID)**	**Articles**
cybersecurity	75	security	38
security	58	management	28
information security	53	model	25
cyber security	33	framework	22
cyber risk	32	risk	22
cyber insurance	31	impact	20
fintech	30	internet	18
machine learning	29	information	13
blockchain	28	performance	13
risk management	26	insurance	12

Source: Authors

Although we consider that the present study provides a comprehensive overview of cyber and operational risks in financial institutions, some conceptual and methodological gaps remain. First, current research continues to treat cybersecurity mainly within institutional boundaries, neglecting the way in which interdependencies between risks spread across financial ecosystems. This highlights the need for studies explicitly modelling cyber-contagion, cross-border exposures and third-party interdependence within financial

networks. Second, while the NEAR/15 approach has allowed us to capture the most powerful conceptual links between cyber security and financial risk, future research could increase coverage by using multiple proximity operators (e.g. NEAR/3, NEAR/10) and extending the analysis to include additional databases such as Scopus or Google Scholar.

Another gap is the geographical asymmetry of research output, which remains concentrated in a few countries. Cross-jurisdictional comparative studies would clarify how the maturity of institutions, regulatory regimes and financial structures affect cyber risk management.

5 Conclusions

The purpose of this study was to explore how cybersecurity has become embedded in the operational risk architecture of financial institutions and to chart the conceptual development of this emerging field of research. Using a systematic bibliometric approach based on PRISMA and using the NEAR/15 proximity operator in the WoS Core Collection, we identified and analyzed 613 unique publications produced between 2001 and 2025. This approach has ensured that the literature provides the strongest contextual links between cyber security, financial institutions, operational risk, systemic vulnerabilities and governance frameworks.

The distribution of research across 453 publications and 75 countries shows a broad international interest, but remains concentrated in a limited number of countries and journals. The co-citation and keyword analyses identified three interlinked themes: (1) quantitative and economic modelling of cyber risk and insurance; (2) empirical and market-based studies on the financial and market consequences of cyber incidents and (3) methodological frameworks applicable throughout the cyber field.

While the current analysis relies solely on the NEAR/15 operator and the WoS database, future research should be built on this basis, by integrating multiple NEAR/x parameters and other databases such as Scopus, Google Scholar or IEEE Xplore. This could offer a more comprehensive and varied perspective of semantic proximity and help capture new literature on the study of cyber risk in the financial sector.

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The Digital State as an Engine of Private Sector Development

Review article

Dominik Vukušić[1], Mitja Durnik[2], Radoslav Barišić[3]

ABSTRACT

The digital state is increasingly recognized as a key enabler of private sector development, especially when supported by a systematic results framework linking public-sector reform to economic outcomes. The paper considers the digital transformation journey as a series of multi-stage events in which focusing on foundational challenges such as service adoption, limited e-services, poor cloud infrastructure, weak start up networks, and deficiencies in digital skills allows for targeted interventions in public service digitization, the building of institutional capacity, and the support of digital entrepreneurship. These activities generate an intermediate effect in the form of extended access to integrated e-government services, increased adoption of national digital platforms, better support for start-ups and MSMEs, and a growing digitally literate workforce. Over time, these have led to tangible outcomes, with higher uptake of digital public services, a rise in private investment and job creation, and increased competitiveness in key sectors, such as offshoring and innovation-driven industries. The analysis provides insight into the necessity of enacting reforms in sequence which increases public-private linkages and inclusiveness, as can be seen in gender-sensitive digital skills development. Finally, the paper contends that the digital state should not simply be conceived as an administrative "enhancement," but as an infrastructure/systemic platform in which infrastructure investments in public policies are linked to sustainable and persistent long-term results, including a more agile, inclusive and resilient economy supported by private sector dynamism.

***Keywords**: Digital state, Digital public infrastructure, Private sector development, E-government, Digital economy*

1 *PhD Student - University of Ljubljana, Faculty of Public Administration, Gosarjeva ulica 5, 1000 Ljubljana, Slovenia / University of Rijeka, Faculty of Economics and Business Ivana Filipovića 4, 51000 Rijeka, Croatia; dv30894@student.uni-lj.si / dvukusic@worldbank.org*

2 *PhD Mentor, Assistant Professor - University of Ljubljana, Faculty of Public Administration, Gosarjeva ulica 5, 1000 Ljubljana, Slovenia / University of Rijeka, Faculty of Economics and Business Ivana Filipovića 4, 51000 Rijeka, Croatia; Mitja.Durnik@fu.uni-lj.si*

3 *Associate Professor - Faculty of Economics and Business, University of Zagreb Trg J.F. Kennedy 6, HR-10000 Zagreb, Croatia, rbarisic@efzg.hr*

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1 Introduction

In times of rapid technological disruption driven by artificial intelligence, cloud computing and data, the digital state acts as a powerful and transformative engine of change toward a sustaining private sector dynamism in both advanced and developing countries (Sharma & Sharma, 2025). It successfully integrates the reform agenda (e.g., bureaucratic efficiency and regulation with national economic growth interests) but also acts in harmony with the economic growth strategy, yielding synergies which enhance the effects of fiscal and policy interventions. Far from being merely an administrative tool that aims to automate internal systems of digitalization in terms of paperwork and simple online portals, the digital state represents a complex of system-level tools that are systematically interconnected (Sharma & Sharma, 2025).

These interventions can range from basic infrastructure developments, such as a national broadband internet infrastructure construction, to secure a cloud computing infrastructure for interoperable data architectures and skill building programs (Cooke, 2017). The grand strategy aims to facilitate enduring private investment inflows, stimulate growth in high value sectors, such as the creation of jobs in technology services and manufacturing, and to raise sectoral global competitiveness by empowering firms with innovative tools and scaling to new tools of the trade (Song et al., 2025).

This view is a natural fit with the structured results framework used for international development programs that include many international mechanisms, especially multi-lateral mechanisms, which highlight clear and well-defined indicators for the progress from inputs to outputs, outcomes, and ultimately long-term societal and economic consequences (Hanna, 2018). These models offer a framework not only for policy enactment, but also for ongoing monitoring, evaluation, and adaptive learning so that the interventions can address the changing technological and socio-economic settings. It begins a process of proactive identification and systematic solutions for core hindrances to digital maturation. Among others, these include continuous e-service gaps that frustrate users with broken, erratic, and unreliable government interfaces; restricted, non-uniform, cloud infrastructures that limit storage, processing, and enabling real-time analytics; and widespread digital skills shortages that deny vital sectors new, technology-enabled opportunities (Sharma & Sharma, 2025).

Meeting these challenges require coordinated, layered approaches. By methodically tackling such bottlenecks through selective public investment, public and private partnerships, and thoughtfully crafted incentives for policy compliance, governments will be able to create a foundation platform for more sophisticated e-government ecosystems. These are the tools that can grow into smooth, user-first, all-in-one platforms that streamline and connect accessibility to all sorts of services: from registration and taxation, through procurement and licensing, to the delivery of social welfare, by way of an ever-demanding efficiency, transparency and confidence in public institutions (Cooke, 2017).

Simultaneously, the comprehensive digital innovation scene has to be reinforced. Stronger start up environments can emerge through the development of exclusive incubators and accelerators, the roll-out of regulatory sandboxes that facilitate safe experimentation with new technologies, and improved access to financing through networks that include venture capital and blended funding and other mechanisms. At the same time, the need to develop inclusive entrepreneurship is paramount. Such initiatives that will reduce structural barriers, including limited access to funding, networks and digital tools, for women, rural populations, and other marginalised groups can greatly widen the pool of potential innovators and economic partners. As such, governments not only drive more energetic and diversified growth of the economy but also make certain that the gains of digital transformation are distributed more equally across society (Siddiqui, 2025).

2 Literature review

Researchers across multiple fields, particularly within innovation studies that diverge from the aforementioned study of Hanna (2018), such as innovation economics and public administration, consistently highlight that the state will play a powerful and necessary role, one which can be seen as both proactive and indispensable, in guiding this deep transformation. Hanna (2018) specifically identifies the government as the central driver of digital innovation and claims that soundly calibrated public policies, ranging from spectrum allocation for 5G to antitrust actions to counter digital monopolies, as well as complementary investments in infrastructure are key to solving market dysfunction that the private sector alone cannot tackle. Such state actions create ecosystem conditions for an entrepreneurial activity that de-risks ventures, facilitates access to data fairly, and avoids exclusionary practices that block out competition (Hanna, 2018; Cooke, 2017).

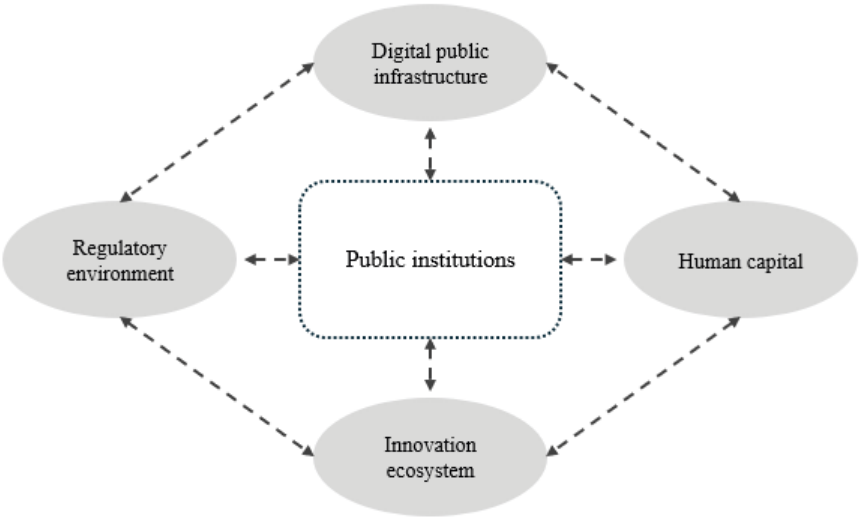
As mainstream public funding sources fray amidst increasing financial and austerity pressures, hybrid models have surged, marrying state stewardship and the mobility of the private sector. Digital technologies have become linchpins at the heart of strengthening public-private collaboration, and Cooke (2017) rightly highlights the need for the state to reverse its traditional role as a dominant service provider to a strategic enabler of economic resilience, a vehicle for shared platforms that propel mutual productivity and adaptability gains.

This evolutionary pattern is particularly evident in concrete paradigms, such as China's digital corporatism, where state-business partnerships have been systematically promoted in the central government policy as the core strategy for strengthening governance capacity (Song et al., 2025). In this context, highly integrated and symbiotic partnerships that are deeply institutionalized and occur between state bureaucracy and technology powerhouses are central in enhancing the digital state capacity. Such collaborations facilitate the adoption of large-scale, surveillance-based data infrastructures along with state-backed analytical tools, providing a more accurate, data-specific approach to governance.

Simultaneously, predictive analytics founded on advanced digital technologies and data-driven methods fortifies anticipatory policy making. Supporting the above advancements, ecosystem-wide technology standards and platforms help to strengthen cooperation across the sectors in regard to innovation as well as scaling. These interlocking dynamics show that digital corporatism is not merely a conventional economic arrangement or policy framework, but rather a far-reaching and deeply embedded model of governance that radically reconfigures relations among state authority, technological capability, and market actors, placing them all in an integrated system of coordination, data exchange and strategic control, which reinforces a combination of administrative capacity and economic dynamism (Song et al., 2025).

These dynamics are equally pronounced in the Global South, where structural vulnerabilities exacerbate the stakes of digital transitions. Siddiqui (2025) argues that this is not less relevant, as market-driven neoliberal reforms, if pursued without safeguards, may exacerbate inequalities by favouring urban elites and tech-savvy cohorts at the expense of the general population.

Figure 1: Public sector foundations of private sector growth



Source: Authors based on Cooke (2017)

As a result, digital states are morally and strategically obliged to actively promote equitable accessibility by infusing gender-specific digital skills development through customized curricula, STEM scholarships for women, and local tech communities, in order to lift underrepresented populations and expand private tech companies (Siddiqui, 2025; Sharma & Sharma, 2025). In BRICS countries, AI governance architectures present powerful exemplars of how strengthened public-private links can activate innovative forces, particularly in high-tech sectors such as software offshoring, biotechnology,

and advanced manufacturing, where collaborative RandD hubs and incentives catalyse leapfrog competitiveness. In the end, the digital state reframes governance not as a static bureaucratic machine, but rather a dynamic engine of multiple stages that encourages a holistic, sustained and progressive economic development (Sharma & Sharma, 2025).

Instead of executing single-piece reforms, it is a process with a structured, iterative approach that gradually addresses structural constraints through diagnosis, pilot programs and selective policymaking interventions. These initial steps are a response to still existing inefficiencies like disorganized service delivery, low interoperability and weak institutional coordination. Based on this premise, the digital state moves toward intermediate outcomes such as the integration of digital public services, the enhancement of micro, small and medium-sized enterprises, support for digital fintechs and digital supply-chain operations, and the strengthening of skills upgrading and institutional capacities toward system-wide institutions (Cooke, 2017; Hanna, 2018). These accumulated changes over time, including infrastructure enhancement, skill development, and ecosystem integration have the potential to yield overall macroeconomic advantages that are further-reaching and sustainable, to the extent that they change a country's long run economy.

Economies become super-agile systems that have learned to rapidly adapt to external shocks, whether geopolitical conflicts, pandemics, or climate shocks. This is achieved through digital systems that make it easier to act proactively while enabling quick decision-making, made possible by real-time data analytics, predictive modelling and interconnected dashboards that allow policymakers and firms to respond faster and more effectively (Song et al., 2025; Bu et al., 2024). Increased transparency, end to end traceability via blockchain and IoT sensors, and seamless data integration from suppliers, logistics, distribution and markets within supply chains, increase resilience better than ever before. This minimises weaknesses like one point failures, reduces downtime costs, and enhances efficiency in inventory management (Bu et al., 2024). At the same time, growth models are widening, as more and clearer digital tools, such as affordable broadband, mobile fintech and e-government services, allow for greater volumes of firms, and particularly MSMEs, as well as individuals to engage in advanced value economic activities. This consolidates the private sector as a dominant driver of innovation, employment and value creation (Siddiqui, 2025; Prachumrasee et al., 2025). Particularly in localized settings, digital public service ecosystems facilitate community level participation via user centred platforms that are more likely to bridge urban-rural distances in order to promote entrepreneurship (Prachumrasee et al., 2025).

ILyina (2025) emphasizes that state regulation plays an essential role in designing the innovation infrastructure through coordinated research and development systems and incentive structures that embed digital capabilities into national infrastructure. Empirical research by Bu et al. (2024) confirms that as the digital economy grows, the growth of regional innovation spillovers, based on human capital, improves firms' adaptability and competitiveness. The digital state, through careful sequencing of reforms, starting from an infrastructure which involves the public, moving through governance of

emerging technologies, and prioritizing solutions that can scale (integrated digital platforms, open data systems), engenders effective collaboration of public and private space. Thus it creates trust, aligns incentives, and mitigates the risks to become a resilient mechanism towards sustainable and private-sector-based economic development in the dynamically changing global environment (ILyina, 2025; Sharma & Sharma, 2025).

The digital state reconfigures essential economic pillars (digital public infrastructure, regulatory environment, human capital, innovation ecosystems) in a framework that combines them into a single, interconnected system, pushing the expansion of the private sector. These pillars are not separate "principles", but are strategically linked by digital governance paradigms that promote coordination, efficiency and scalability. Through harnessing the wealth of connectivity data and interoperable platforms, the digital state is able to combat longstanding global inequality while enhancing a nation's competitive position and economic resilience (ITU, 2025). Ultimately, these pillars form the structural underpinning to the transformation towards an industrial-digital technological order in which data, connectivity, and innovation are cornerstones of value creation and economic organization (Mishchenko et al., 2025). Digital public infrastructure is the foundation of this shift, and provides the technological and institutional grounds on which modern economies rest.

Despite the rapid increase in world-wide connectivity (approximately 74% of the world's population was online in the year 2025), inequities in terms of access and quality remain significant, especially in low- and middle-income countries (ITU, 2025). Even as 5G and other high speed technologies are highly concentrated in advanced economies, the role of the digital state is crucial for equitable access and prevention of deeper digital divides. Simultaneously, human capital becomes a fundamental restriction and a force for digitalisation. However, digital skills gaps remain and are still shaped by gender and urban–rural divides. Governments have an important, transformative role in confronting these challenges through comprehensive reforms in education, focused re-skilling, accessible and inclusive digital access policies, and digital technologies that can benefit the labour market. Enhancing human capital does not only lead to better employability but also increases firm-specific productivity and thus supports the diffusion of digital technologies throughout the economy (OECD, 2025; ITU, 2025).

3 Methodology

The analytical framework of this study focuses on organizing heterogeneous sources of data to produce a fine-grained and detailed project/comparative analysis. Key to this approach is the use of primary data, the World Bank Group Task Team Leader (TTL) surveys, as well as an in-depth analysis of internal project documents. In addition, the content of these documents gives direct and context-specific insights into the design, the models of implementation and the outputs of digital development interventions as well as the mechanisms by which private capital mobilization is achieved. Through practitioner-authored evidence, the study is able to reflect the practical complexities, institutional limitations and context differences which influence project performance in different contexts.

To augment this main evidence, the research employs secondary data from international benchmarks such as the OECD Digital Government Index. These benchmarks provide standardized and methodologically robust indicators of digital government maturity, which can be cross-culturally analysed systematically. Moreover, the empirical framework draws on critical engagement with the academic literature, placing thus the findings in context, both with respect to established theoretical paradigms and prior empirical research and as a foundation for analytic triangulation.

Table 1: Systemic effects of digital state pillars on private sector development

Digital state pillar	**Key public interventions**	**Transmission mechanisms to private sector**	**Private sector outcomes**
Digital Public Infrastructure	Broadband expansion, cloud systems, digital identity, data platforms	Reduced transaction costs, improved connectivity, data access	Increased firm productivity, market expansion, innovation
Regulatory Environment	Digital governance frameworks, data regulation, e-government policies	Legal certainty, reduced compliance burden, trust building	Higher private investment, formalization, competition
Human Capital	Digital skills training, education reform, reskilling programs	Skilled workforce supply, adaptability to new technologies	Employment growth, productivity gains, sector upgrading
Innovation Ecosystem	Startup support, public-private partnerships, funding schemes	Knowledge spillovers, access to finance, entrepreneurial support	Startup creation, MSME growth, technological innovation

Source: Authors based on Cooke (2017)

This multimethod data integration promotes a two-level analytical framework. At the micro level, it enables a descriptive-analytically rigorous look at project-specific dynamics, particularly at how digital development and private sector participation interact. On a macro scale, the convergence between project-level evidence and country-level indicators leads to a comparative assessment of digital state maturity across national settings. The latter in turn facilitates a systematic exploration into the relationship between digitalization in the public sector and the outcomes in the private sector, enriching our knowledge of the context in which digital transformation might motivate private capital generation.

In addition to its methodological framework, the analysis also defines systemic effects of digital state pillars on private sector development frameworks (see

Table 1), using secondary literature to situate findings at the project level in context. The state-backed digital platforms, targeted startup policies, and broader access to digital infrastructure are found to be helpful in paving the way for the entrepreneurial environment, in particular, for micro, small, and medium-sized enterprises, as well as enhancing in terms of access to finance, markets, and global value chains (Sharma & Sharma, 2025).

These ecosystems facilitate knowledge diffusion, collaboration, and the scaling of innovative solutions across sectors. Empirical evidence indicates that broadband affordability, reliable connectivity, and open digital environments are critical enablers of innovation and business dynamism, although persistent disparities in access continue to constrain their full impact, especially in developing economies (ITU, 2025). In parallel, effective digital governance ensures that these transformations are strategically coordinated, inclusive, and resilient over time. Advanced digital states demonstrate strong integration of digital identity systems, interoperable data-sharing frameworks, and user-cantered public services, which enhance transparency, build trust, and improve efficiency in interactions between governments and businesses (OECD, 2025). Governance also plays a central role in setting standards, safeguarding data, and fostering accountability within digital ecosystems.

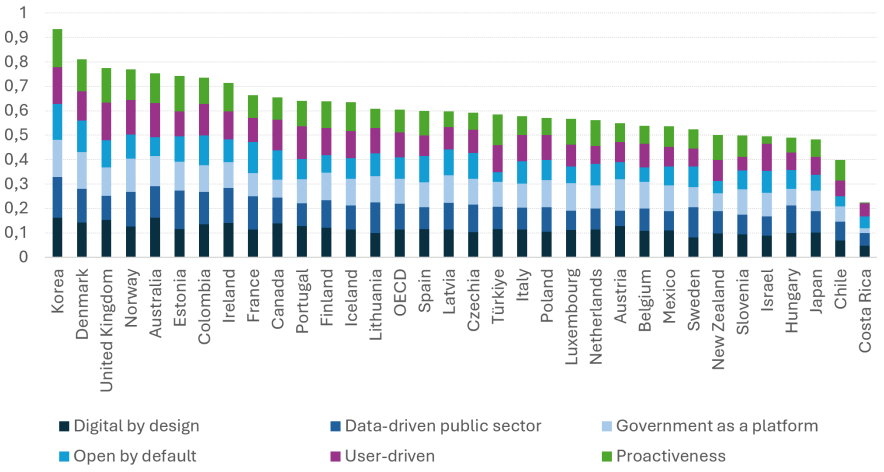
As emphasized by Mishchenko et al. (2025), governance functions as the coordinating mechanism that aligns all key pillars into a coherent and functional system, enabling synergies between technological innovation, institutional capacity, and economic development while ensuring long-term sustainability and adaptability of the digital transformation process. Taken together, these elements highlight how the digital state operates as a structured and multi-layered engine that not only enables private sector development but also sustains inclusive, innovation-driven economic growth.

4 Results

The OECD indicators show significant variation in the level of digital government maturity across countries, revealing that there is an uneven pace at which the global digital state is developing. The OECD Digital Government Index (DGI), presented in Government at a Glance 2025, provides a comprehensive and multidimensional framework to measure how effective governments are at integrating various digital technologies in public administration and service delivery (OECD, 2025).

The DGI captures core dimensions from digital-by-design to data-driven governance, openness, user centricity, and proactiveness, and provides a way to systematically compare how digital transformation feeds into broader economic and institutional outcomes. Results showed that countries scoring high on the DGI indicate stronger alignment between digital governance and important economic variables such as infrastructure development, human capital formation, and innovation capacity.

Figure 2: OECD Digital Government Index



Source: Authors based on OECD (2025)

Advanced models of digital-by-design governance are exemplified in top-performing countries like Korea, with a DGI score of 0.94, and Denmark, with a DGI score of 0.81. In these cases, robust performance across all dimensions is linked to well-integrated digital ecosystems with government platforms that are interoperable, data flowing freely between institutions, and services being proactively delivered to users. These attributes are connected to improved connectivity outcomes such as near universal broadband coverage and reduced gender and regional disparities in digital participation, as well as more inclusive access to digital services (OECD, 2025; ITU, 2025).

Significantly, these pioneering countries illustrate strategic sequencing of reforms, building the foundations for future, consistent support of skills training, regulatory certainty, and innovation programming with an emphasis on early investments in digital infrastructure. This is consistent with Hanna (2018) who posits that state is a catalyst which helps to prevent market collapse and supports private sectors to join in and with Mishchenko et al.'s (2025) industrial-digital development approach when joint public-sector interventions set the stage for dynamic and competitive private industry structures.

Meanwhile middle-income laggards demonstrate DGI rates averaging around 0.61, characterized by fragmented e-services and skills gaps that keep global problems alive (OECD, 2025; ITU, 2025). This empirical void supports Cooke's (2017) case for hybrid public-private approaches in the wake of funding cuts and is demonstrated in the BRICS settings where the use of AI policies has led to greater resilience.

The index is additionally reinforced by the digital corporatism in China that results from state-business synergy on capacity-building under neoliberal pressures in the Global South (Song et al., 2025; Siddiqui, 2025). In general,

the DGI metrics confirm the digital state's transformation of "public" reforms into private growth, as leaders achieve (20-30%) higher indices of innovation (OECD, 2025). Supporting OECD findings, EU-focused reflections extend these trends by offering a more specific view of the digital transformation taking place in different institutions and economic environments. Roszko-Wójtowicz et al. (2024) show that determinants of digital economy growth, especially the technological ecosystem, human capital, and innovation capabilities, differ remarkably between the member states of the European Union between the years 2017 and 2022.

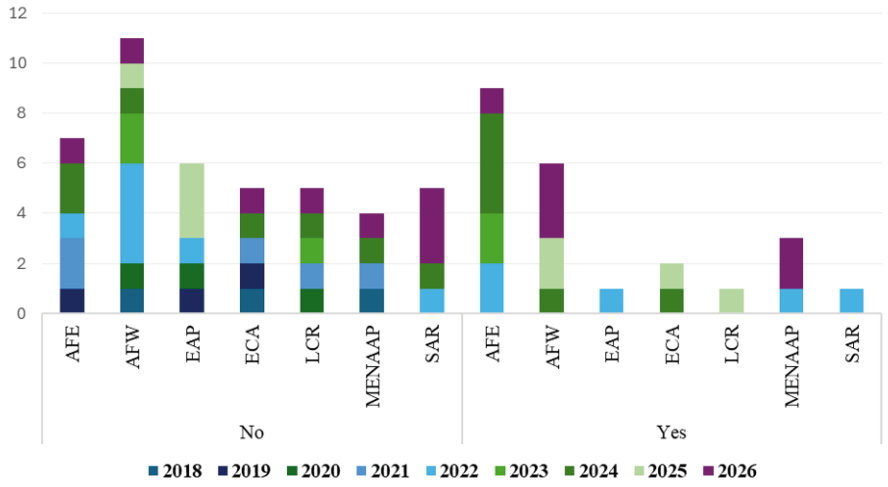
These disparities result in asymmetric economic responses, in particular digital sectors and their investment in national GDP. Successful countries like Estonia have exploited integrated digital ecosystems including mature e-government services, distributed digital literacy and innovative regulatory environment to achieve exceptional performance and promote private sector digitalization. Lagging countries, to date, face structural limitations associated with fragmented infrastructure, limited digital capabilities, and poor institutional coherence, slowing the diffusion of digital technologies and diminishing their economic contribution (Roszko-Wójtowicz et al., 2024).

Ofe and Sandberg (2023) also contribute important data on how governance changes through such disruption in sectors, specifically Swedish public transport systems in digital transformation. This analysis shows the emergence of digital ecosystem governance frameworks which seek more flexible and responsive use of public and private actors, adopting adaptive and collective arrangements. Systems, through coordinated deployment of digital platforms, coordinated use of technology to support interoperability, data flows, and real-time monitoring mechanisms, can reinstate activity and control, enhance service continuity, optimize service delivery efficiency, and provide improved user experience even when a business is affected by disruption.

Results are in line with the overall data coverage of trends from the broader OECD Digital Government Index, which points to proactive governance, interoperability, and user-focused service design. Collectively, this evidence supports the strong impact of a digital state that can integrate infrastructure, skills, and governance into coherent frameworks for facilitating and aligning data flows on resilience when addressing shocks, innovation and enhancing the state and private sector competitiveness in a digitally connected and network-enabled global economy (OECD, 2025; Roszko-Wójtowicz et al., 2024).

The review of 66 World Bank Group (WBG) digital development operations is grounded on a systematic examination of primary, project-level, TTL (Task Team Leader) primary survey data coupled with WBG project documentation. Each project is allocated by region, year, and whether it has a component of private capital mobilization (PCM). The approach summarizes activities by region (Africa East, Africa West, South Asia, etc.) and follows performance trends (2018-2026), with or without PCM projects being shown. This enables a closer examination of the extent to which private capital is tapped into for digital development and how this varies by geographic location.

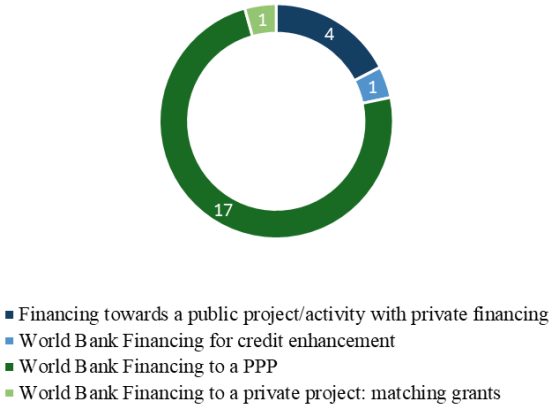
Figure 3: World Bank digital development operations by region and PCM



Source: Authors based on TTL survey

The approach is descriptive and counts operations under categorization in line with PCM involvement and product type and not causal impacts. This begins with government-initiated financing or with state-owned entities seeking private financing in a project, including both commercial financing and funding from the World Bank, i.e., financing towards a public project in combination with private financing.

Figure 4: World Bank digital development operations by PCM product



Source: Authors based on the TTL survey

Second, we have World Bank credit enhancement instruments, including guarantees or a facility for risk-sharing, to help diminish risk and bring in private investment. Third, there is the World Bank financing for the establishment of a

PPP (public-private partnership) in which private companies invest equity and/or debt into some form of infrastructure or service delivery within a contractual agreement with government. Fourth, includes the World Bank financing of a private project via matching grants, in which there is a combination of Bank funds and private co-investment to stimulate firms or innovation (World Bank Group, 2021). These lines also cover the primary channels through which WBG's activities funnel private capital into digital development.

5 Conclusions

This paper has shown that the digital state signals a fundamental drive for public institutions to evolve from traditional, administrative institutions to a dynamic ecosystem that shapes the development of the private sector. The digital state, by combining digital public infrastructure, regulatory systems, human capital development, and innovation ecologies, constructs a dynamic and mutually reinforcing mechanism for economic growth. And these do not operate separately but are intertwined as well as interdependent by mechanisms of governance that act as the glue that pull and align interventions so as to alleviate the structural restraints and to facilitate more efficient links between public and private entities.

The study underscores that digital transformation is not only a technology, but also an economic strategy that fundamentally transforms value creation, distribution, and sustainability in contemporary economies. The empirical evidence, including evidence from OECD Digital Government Index indicators, further supports the opinion that stronger private sector outcomes are significantly accompanied by higher levels of digital government maturity. The countries that embrace a digital-by-design attitude and focus on integrated platforms, capacities, and regulatory clarity are more creative, more productive and more competitive as a business. On the other hand, if there are scattered networks and entrenched disparities in ownership and access to technology, then these institutions pose structural barriers to private sector growth.

Findings underline the need to sequence reforms, develop fair digital infrastructure and build institutional capacities so that the digital transformation can materialize into economic benefits. In addition, the paper emphasises the significance of inclusivity as well as resiliency in the digital transformation process. Persistent inequalities in access to digital technology and skills, especially within genders and geographical locations, continue to pose a significant challenge. We need to address these disparities not only as a societal obligation, but also from an economic standpoint, as wide-ranging participation makes the sector more productive and innovative. And equally important is a strong governance that helps manage risks in data security, privacy, and regulatory fragmentation, so that we can maintain trustworthy and sustainable digital ecosystems.

As a whole, the evidence indicates that though state digitalization has emerged as a global priority, most countries are in a state of transition where public financing is the dominant form and private capital inflows are selective and uneven. Non-PCM operations demonstrate that many states are still constructing foundational digital systems, connectivity, and core platforms, in

the public context before private capital begins crowding in. Where private engagement happens, it is focused more on a small set of tools, most visibly public-private partnerships, suggesting a lack of diversification in the way states interface with markets. This pattern shows both advancement and the gaps: while governments are pushing digital transformation regionally, institutional capacity, regulatory frameworks, and risk-sharing mechanisms are yet to mature enough for private capital to expand and catalyse a more cohesive global role in states' digitalisation. Its success hinges on the capacity of governments to reconcile public-private coalitions in infrastructure operations, public sector reforms, skills upgrading and innovation policies into a common policy framework. In this digital economy of growing digitalisation, the role of the state as a platform, orchestrator and enabler, will matter heavily if we are to be competitive long term in the economy and achieve inclusive growth. Research should further investigate the causal links between particular digital policies and private sector performance and when digital transformation can best facilitate sustainable economic development in different national settings.

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Part III: Sectoral Digital Transformation and Managerial Capacity

Integration of Digital Marketing Tools into Global Agribusiness Development Processes

Original scientific paper

Nataliia Parkhomenko[1]

ABSTRACT

In today's conditions of globalization and digitalization, the agricultural sector is faced with the need to implement innovative approaches to increase competitiveness. Digital marketing tools are becoming important factors in the integration of agricultural products into international markets. The main goal is to determine the role and effectiveness of digital marketing tools in the global development of the agricultural sector, as well as to identify prospects for their integration in order to build sustainable competitive advantages. To achieve the set goal, a comprehensive approach was applied, including qualitative and quantitative research methods. The online survey of consumers was conducted to assess the level of trust in agricultural products and their willingness to make purchases through digital channels. The statistical analysis of sales and export data on agricultural products was performed in the context of digital marketing use. The regression analysis was applied to identify the correlations between digital advertising costs and sales volumes. In addition, a comparative analysis of international experience and content analysis of scientific publications and practical cases from agricultural companies were used. The study showed that digital marketing tools significantly increase the efficiency of agricultural producers' access to foreign markets, they contribute to increased transparency of supply chains and build trust in brands. The use of social media and e-commerce platforms provides direct access to end consumers, while data analytics helps forecast demand and reduces risks. At the same time, there are challenges associated with digital inequality and limited access of small farmers to digital technologies. The integration of digital marketing tools into global processes of agricultural sector development is a strategically important factor in increasing its competitiveness. The use of digital technologies helps optimize the interaction between producers and consumers and enhances the effectiveness of product promotion.

***Keywords**: Agricultural sector, Digital marketing, Digitalization, Competitiveness, International markets*

1 *Associate professor, Comenius University in Bratislava, Faculty of Management, Odbojárov 10, 82018, Bratislava, Slovak Republic. Scientific affiliation: Comenius University in Bratislava, Simon Kuznets Kharkiv National University of Economics. E-mail: nataliia.parkhomenko@fm.uniba.sk*

***JEL classification**: F23, F63, M31, O13, Q13*

1 Introduction

The digital transformation of agribusiness has become a central theme in contemporary economic and management research. Existing studies demonstrate that digital technologies enhance productivity, transparency, and sustainability in agricultural value chains (Shamshiri et al., 2024; OECD, 2021). A growing body of literature further emphasizes the role of digital platforms, e-commerce, and social media in connecting farmers with markets and end consumers (Giampietri & Trestini, 2020; Appel et al., 2020; Morepje et al., 2024). From a theoretical perspective, these processes are commonly interpreted through the Technology–Organisation–Environment (TOE) framework and the diffusion of innovations theory, which explain adoption decisions as a function of technological readiness, organizational resources, and environmental pressures (Rogers, 2003; Giampietri & Trestini, 2020).

Despite this progress, the literature remains fragmented in three important respects. First, most studies focus on technological adoption or platform usage at the farm level, while the strategic role of digital marketing in shaping international competitiveness and export performance remains under-theorized. Second, empirical research is dominated by qualitative case studies or single-country analyses, providing limited comparative evidence across heterogeneous digital ecosystems. Third, existing models rarely integrate marketing analytics with broader theories of competitive advantage, leaving unclear how digital marketing capabilities function as strategic resources in global agribusiness.

This paper addresses these gaps by arguing that digital marketing capabilities can be interpreted as strategic resources in the sense of the resource-based view (Barney, 1991), as they enable companies to differentiate their market communication and strengthen their relationships with international consumers. At the same time, these capabilities can function as diffusion mechanisms within heterogeneous institutional environments (Rogers, 2003). Building on these theoretical foundations, the study develops an integrated analytical framework that links digital marketing investments, digital maturity, and consumer trust to export performance in agribusiness. Methodologically, the paper combines cross-country survey data, secondary export statistics, and multivariate regression modelling, complemented by comparative case analysis across five countries with different levels of digital maturity.

By doing so, the study makes three contributions. First, it advances theory by positioning digital marketing not merely as an operational tool but as a strategic capability that mediates between technological adoption and international competitiveness. Second, it provides quantitative evidence on the relationship between specific digital marketing inputs and export outcomes, which remains scarce in the agribusiness literature. Third, it offers a comparative perspective that reveals how the effectiveness of digital marketing strategies varies across institutional and infrastructural contexts.

The purpose of the study is therefore to determine the role and effectiveness

of digital marketing tools in the global development of the agricultural sector and to identify how their integration can generate sustainable competitive advantages. In addressing this objective, the paper contributes to a more systematic understanding of digital marketing as a driver of structural transformation in global agribusiness.

2 Literature review

2.1 Digital transformation in agribusiness

Recent research conceptualizes the digital transformation of agriculture as a systemic process integrating technological, organizational, and market-level change (Shamshiri et al., 2024; OECD, 2021). Beyond precision farming and data-driven production, digitalization increasingly reshapes value chains, market access, and competitive structures in agribusiness.

The Technology–Organisation–Environment (TOE) framework is frequently applied to explain adoption patterns, emphasizing the role of technological readiness, organizational resources, and environmental pressures (Giampietri & Trestini, 2020). In this perspective, digitalization is not a purely technical phenomenon, but a strategic process embedded in institutional and market contexts.

2.2 Digital marketing tools in agricultural markets

Digital marketing tools, such as social media, e-commerce platforms, search engine optimization, and content marketing, are increasingly central to market access in agribusiness (Appel et al., 2020; Kanellos et al., 2024). Studies show that these tools enable direct interaction with end consumers, reduce dependency on intermediaries, and enhance brand visibility.

E-commerce platforms are particularly important for small and medium-sized producers, as they lower entry barriers to regional and international markets (Morepje et al., 2024; Kong et al., 2024). However, their effectiveness depends on complementary infrastructure, logistics, and digital skills (Schwering et al., 2022).

2.3 Consumer behaviour in digital agrifood contexts

In digital environments, consumer behaviour is shaped by perceptual and relational mechanisms. Trust has been identified as a central prerequisite for online purchasing, particularly in markets characterized by product quality uncertainty, such as food and agricultural goods (Park & Kim, 2022). Satisfaction with digital purchasing experiences fosters repeated interactions and reduces perceived risk (Appel et al., 2020).

Loyalty and repurchase intention represent behavioural outcomes of successful digital interaction. Prior studies demonstrate that satisfaction and trust are strongly associated with loyalty and intention to repurchase in online contexts (Palaniswamy & Raj, 2022; Kanellos et al., 2024). In agrifood

markets, these mechanisms are particularly salient due to the importance of safety, origin, and transparency.

2.4 Digital marketing and export performance

While a growing literature links digitalization to productivity and market access, empirical evidence on the relationship between digital marketing and export performance remains limited. Existing studies typically focus on technological adoption or platform participation at the farm level (Giampietri & Trestini, 2020; Qiu et al., 2025).

Macro-level analyses rarely integrate consumer-level mechanisms with structural indicators such as export dynamics. As a result, the pathways through which digital marketing contributes to international competitiveness in agribusiness remain under-theorized.

2.5 Research gap and hypotheses

Despite extensive research on digitalization in agriculture, three gaps remain. First, consumer-level mechanisms, such as trust, satisfaction, loyalty, and repurchase intention, are rarely integrated into export-oriented models of agribusiness development. Second, macro-level studies of digital marketing investment and export performance are typically detached from consumer behaviour research. Third, cross-country evidence combining both analytical levels is scarce.

This study addresses these gaps by integrating consumer survey data with macro-level indicators of digitalization and export performance in a unified analytical framework.

Based on the literature, the following hypotheses are proposed:

H1: Brand trust is positively associated with online satisfaction.

H2: Online satisfaction is positively associated with digital loyalty.

H3: Digital loyalty is positively associated with repurchase intention.

H4: Digital marketing investment, online consumer engagement, and digital maturity are positively associated with export performance.

3 Methodology

3.1 Research design and purpose

The study follows a cross-sectional explanatory research design aimed at examining how digital marketing capabilities affect export performance in agribusiness through consumer-level mechanisms of trust, satisfaction, loyalty, and repurchase intention. The analytical framework is grounded in the resource-based view (Barney, 1991), which conceptualizes digital marketing capabilities as strategic resources, and in diffusion of innovations theory (Rogers, 2003), which explains cross-country heterogeneity in adoption and effectiveness.

The empirical model integrates two levels of analysis. At the consumer level, perceptual constructs capture digital trust and behavioural intentions. At the country level, secondary indicators reflect digital marketing investment, online consumer engagement, and digital maturity of agribusiness. Export performance serves as the dependent macro-level outcome.

The analytical logic of the study assumes that consumer-level mechanisms represent the micro-foundations of export performance. Digital trust, satisfaction, and loyalty increase the effectiveness of digital marketing channels by strengthening brand – consumer relationships and facilitating repeat purchasing. When aggregated at scale, these mechanisms contribute to higher online engagement and market reach, which can ultimately translate into stronger export performance. Thus, the consumer-level analysis provides behavioural insight into the mechanisms that may underpin the macro-level associations observed in export data.

To reduce conceptual ambiguity, all survey-based constructs refer to a single, concrete consumption episode. Specifically, respondents were instructed to evaluate their most recent online purchase of an agricultural or food product made via a digital channel (within the last months). This anchoring procedure ensures that respondents assess a specific brand, product, and digital context, avoiding generalized or abstract judgments about all brands or all channels. Accordingly, all consumer-level inferences in this study refer to users of digital channels for purchasing agricultural products rather than to national populations as a whole.

3.2 Sampling and data collection

Primary data were collected through an online survey conducted between April and June 2025 in five countries: Ukraine, Slovakia, Germany, Italy, and Kenya. These countries were selected to represent heterogeneous levels of digital maturity in agribusiness and differing institutional environments. The target population consisted of adult consumers (18+) who had purchased an agricultural or food product online at least once in the preceding 12 months. This inclusion criterion ensured that all respondents had actual experience with digital purchasing channels.

A non-probability sampling strategy was employed, combining convenience and judgmental sampling with quota controls for age group, gender, and frequency of online purchases. The sampling frame was not the general population but users of digital channels for purchasing agricultural or food products. Quotas were applied to approximate the structure of this specific population of digital agrifood consumers rather than national populations. Accordingly, the sample cannot be considered representative of the general populations of the five countries, and the results are generalizable only to consumers who actively use digital channels for purchasing agricultural products. Responses that violated quota constraints or failed attention checks were excluded.

The final sample consisted of 495 valid observations (Ukraine: 111; Slovakia: 98; Germany: 101; Italy: 93; Kenya: 92). Cases with incomplete

questionnaires, straight-lining patterns, or completion times below one-third of the median were excluded (n = 37). This balanced country distribution was intentionally achieved to support the reliability of cross-country comparisons within the defined population of digital agrifood consumers. Given that an identical questionnaire was used in all five countries, instrument validation was conducted at an early stage of the research process. A pilot study (n = 42) was carried out to assess item clarity, response patterns, and preliminary reliability across language versions. Data were collected using Google Forms. Secondary data on exports, digital investment, and macroeconomic indicators were obtained from FAOSTAT, OECD Data, the World Bank Open Data, and publicly available company reports.

3.3 Construct definition and operationalization

Four latent constructs were examined at the consumer level:

- Brand Trust – the degree to which the consumer perceives the agricultural brand as reliable, honest, and competent in the digital environment.
- Online Satisfaction – the overall affective evaluation of the digital purchasing experience with the selected brand.
- Digital Loyalty – the consumer's intention to continue purchasing the same brand via digital channels.
- Repurchase Intention – the likelihood of buying the same product again online soon.

All constructs were measured using established multi-item scales adapted to the agrifood context.

At the macro level, three independent variables were operationalized using secondary data:

- Digital marketing investment (X_1) – national-level spending on digital advertising in agrifood sectors.
- Online consumer engagement (X_2) – number of active online buyers of agricultural products.
- Digital Maturity Index (X_3) – a composite indicator reflecting customer relationship management usage, analytics integration, platform diversity, and automation level in agribusiness.

Export volume of agricultural products served as the dependent variable (Y).

3.4 Reliability, validity and common method bias

Internal consistency was assessed using Cronbach's alpha, Composite Reliability (CR), and Average Variance Extracted (AVE). All constructs exceeded recommended thresholds ($\alpha > 0.80$; $CR > 0.85$; $AVE > 0.60$).

Discriminant validity was tested using the Heterotrait–Monotrait (HTMT) ratio.

All HTMT values were below 0.85, indicating adequate construct separation.

Several procedural remedies were implemented to reduce common method bias and social desirability effects: psychological separation of predictor and criterion variables; randomized item order; assurance of anonymity and non-evaluative purpose; neutral wording and avoidance of normative statements.

Statistically, Harman's single-factor test indicated that the first factor accounted for less than 32% of total variance, suggesting that common method bias is unlikely to threaten the results.

3.5 Analytical tools

Data processing and analysis were performed using SPSS 27 for descriptive statistics, reliability testing, and regression modelling; R (lavaan package) for construct validation and HTMT computation; Excel for secondary data harmonization.

Given the limited number of observations available in the country-level dataset (five countries over the period 2020–2024), the regression model should be interpreted as an exploratory analytical tool rather than as a basis for strong causal inference. The purpose of this model is to illustrate potential directional relationships between digital marketing activity and export dynamics rather than to estimate precise causal effects.

4 Empirical data and analysis

The empirical analysis is based on a combination of primary survey data and secondary macroeconomic indicators describing digital marketing activity and export performance in agribusiness across the selected countries.

The primary dataset consists of survey responses from 495 consumers in five countries: Ukraine, Slovakia, Germany, Italy, and Kenya. The survey focuses on individuals who have purchased agricultural or food products through digital channels such as e-commerce platforms or producers' websites. The collected data capture consumers' perceptions of brand trust, satisfaction with online purchasing experiences, digital loyalty, and intentions to make repeat purchases.

In addition to the survey data, the study incorporates secondary statistical indicators reflecting the level of digital marketing investment, the number of online consumers purchasing agricultural products, the Digital Maturity Index of agribusiness companies, and the export performance of the agricultural sector. These indicators were obtained from international statistical databases, including FAOSTAT, OECD Data, and the World Bank Open Data, as well as publicly available industry reports.

The integration of consumer-level behavioural data with macro-level indicators allows for a multi-level analysis of the role of digital marketing tools in shaping competitiveness and export dynamics in agribusiness.

5 Results and discussion

All perceptual constructs refer to respondents' most recent online purchase of an agricultural or food product made via a digital channel within the three previous months. Internal consistency and convergent validity were assessed using Cronbach's alpha (α), Composite Reliability (CR), and Average Variance Extracted (AVE). All constructs exceeded recommended thresholds (α > 0.80; CR > 0.85; AVE > 0.60). Discriminant validity was examined using the Heterotrait–Monotrait (HTMT) ratio. All HTMT values were below 0.85, indicating adequate construct separation and absence of conceptual overlap between Trust, Satisfaction, Digital Loyalty, and Repurchase Intention. The reliability and validity of the measurement model are summarized in Table 1. The table reports factor loading ranges (λ), Cronbach's alpha (α), Composite Reliability (CR), and Average Variance Extracted (AVE) for each construct, providing evidence of internal consistency and convergent validity.

Table 1: Measurement Model: Reliability and Validity of Perceptual Constructs

Construct	Items (λ)	α	CR	AVE
Brand Trust	0.74–0.86	0.88	0.90	0.69
Online Satisfaction	0.72–0.84	0.86	0.89	0.66
Digital Loyalty	0.75–0.88	0.89	0.92	0.72
Repurchase Intention	0.73–0.87	0.87	0.90	0.68

Source: Author

All constructs demonstrate satisfactory internal consistency and convergent validity, exceeding recommended thresholds, while HTMT values confirm adequate discriminant validity among the four perceptual constructs.

The online survey covered 495 consumers in five countries (Ukraine, Slovakia, Germany, Italy, and Kenya) who had purchased an agricultural or food product online within the previous three months. All responses refer to one concrete purchase episode via a digital channel (e-commerce platform or producer's website), ensuring that perceptions of trust, satisfaction, loyalty, and repurchase intention are anchored in a specific brand and product context. The sample is representative in terms of basic socio-demographic parameters. Thus, the ratio of respondents by gender is 52% women and 48% men; by age, 22% are 18–29 years old, 39% are 30–44, 27% are 45–59, and 12% are 60+; by level of education 68% have higher education, 32% have secondary education; and by the frequency of online purchases, 24% buy agricultural products every week, 41% once a month, 35% less often. Respondents demonstrate different value orientations. For example, consumers from Ukraine and Kenya are more price-sensitive, while in Germany and Italy, attention to ethical and environmentally friendly production prevails.

A five-point Likert scale (1= strongly disagree, 5= strongly agree) was used to analyse trust and attitudes towards digital channels. Indicators of trust in brands, satisfaction with the online shopping experience, loyalty to digital

channels and intentions to make repeat purchases were measured. The mean values represent evaluations of a single, recently purchased agricultural product and its brand in a specific digital channel. The average values of consumer behaviour indicators are given in Table 2.

Table 2: Average values of consumer behaviour indicators (by country)

Country / Indicator	Ukraine	Slovakia	Germany	Italy	Kenya	Average value
Brand Trust	3.42	3.78	4.15	4.09	3.35	3.76
Online Satisfaction	3.51	3.82	4.21	4.10	3.48	3.82
Digital Loyalty	3.26	3.70	4.05	3.92	3.21	3.63
Repurchase Intention	3.60	3.95	4.32	4.18	3.41	3.89

Source: Author

The highest average trust and satisfaction scores are recorded in Germany (4.15; 4.21) and Italy (4.09; 4.10), indicating the maturity of the digital infrastructure, the reliability of online platforms and a positive user experience. Slovakia has a medium level of stability in indicators, while Ukraine and Kenya have moderate trust, indicating the need for increased transparency of product information and improved after-sales service.

The behavioural aspects of agricultural product consumption were analysed. Respondents evaluated the influence of each digital channel on their most recent purchase decision using a five-point scale (1 = not influential at all; 5 = very influential). This allows direct comparison of channel effectiveness across countries and demographic groups. The respondents identified the following channels for obtaining information: social networks (average = 3.92), official websites of manufacturers (3.42), online marketplaces (3.78) and recommendations from friends and bloggers (2.81). It was found that social networks are a key source of communication, especially among younger consumers (18–34 years old). For Germany and Italy, official websites of brands are a priority, while in Ukraine and Kenya the main flow of purchases goes through marketplaces. The ANOVA tests indicate statistically significant cross-country differences in perceived channel influence ($p < 0.05$), with social media being most influential among younger consumers, while official brand websites dominate in Germany and Italy.

All evaluations refer to the specific product purchased online by the respondent. Respondents were asked to rate the importance of selected product attributes in their most recent online purchase of an agricultural product on a five-point scale (1 = not important at all; 5 = very important). The results of the assessment are presented in Table 3.

Table 3: Descriptive importance of product attributes in recent online purchases of agricultural products

Factor (Product attribute)	Average score	Rating
Product quality	4.65	1
Price	4.42	2
Environmental friendliness	4.08	3
Production transparency	3.92	4
Brand Trust	3.85	5

Source: Author

These results describe the relative importance of basic product attributes in recent online purchases. They are descriptive in nature and should not be interpreted as predictors within the structural model. Thus, quality and price remain the determining factors influencing the motives for purchasing decisions, while the importance of environmental friendliness and production transparency is increasing, which is a result of the increased attention to sustainable consumption. The results indicate that trust-related perceptions are positively associated with purchase intentions. However, the present analysis does not allow for causal inference regarding the effect of digital maturity signals in the digital environment.

The results of the correlation analysis by consumer behaviour parameters are presented in Table 4.

Table 4: Correlation analysis of variables ($p < 0.01$)

Indicator	Brand Trust	Online Satisfaction	Digital Loyalty	Repurchase Intention
Brand Trust	1.00	0.68	0.64	0.59
Online Satisfaction	0.68	1.00	0.71	0.63
Digital Loyalty	0.64	0.71	1.00	0.69
Repurchase Intention	0.59	0.63	0.69	1.00

Source: Author

Strong positive relationships are observed between all constructs. In particular, the highest correlation is found between Satisfaction and Digital Loyalty ($r = 0.71$), followed by the association between Loyalty and Repurchase Intention ($r = 0.69$). Correlation analysis reveals strong and statistically significant associations between Trust, Satisfaction, Digital Loyalty, and Repurchase Intention ($p < 0.01$). These relationships suggest potential predictive links, which are further examined in the regression models.

To provide a contextual background for the subsequent macro-level analysis, country-specific differences in digital ecosystems were reviewed using

secondary sources. These observations serve as descriptive context and do not constitute inferential results. The core empirical relationships are therefore examined below using multivariate regression models based on harmonized secondary data. The regression analysis is based on secondary panel data for 2020–2024 obtained from FAOSTAT, OECD Data, the World Bank Open Data, and annual reports of representative agribusiness companies in each country. The dataset includes export volume of agricultural products, national-level digital advertising expenditure in agrifood sectors, the number of active online buyers, and the Digital Maturity Index. Table 5 presents the descriptive statistics for all variables included in the regression model.

Table 5: Descriptive statistics of regression variables

Variable	Mean	SD	Min	Max
Exports (USD bn)	46.8	32.4	7.2	118.5
Digital ad spend (USD m)	214.6	165.3	28.4	520.7
Online consumers (thousands)	4,320	3,180	610	11,450
Digital maturity index	0.72	0.14	0.48	0.91

Source: Author according to FAOSTAT, OECD Data, and World Bank Open Data

For an in-depth analysis of the relationship between the level of digital activity of agricultural companies and their export results, a multivariate linear regression model was constructed.

During the diagnostic process, a correlation analysis was conducted between variables to check for multicollinearity (Table 6).

Table 6: Correlation analysis between variables of the regression model

Indicators	X_1	X_2	X_3	Y
X_1 – Digital advertising spending	1.00	0.87	0.80	0.91
X_2 – Online consumers	0.87	1.00	0.78	0.89
X_3 – Digital maturity index	0.80	0.78	1.00	0.86
Y – Agricultural exports	0.91	0.89	0.86	1.00

Source: Author

All predictors have a strong positive relationship with the outcome variable (Y). However, the correlation coefficients are lower than 0.9, which allows us to consider the multicollinearity acceptable.

Given the relatively high pairwise correlations between predictors reported in Table 6, additional multicollinearity diagnostics were performed. To further assess potential multicollinearity among the independent variables, Variance Inflation Factor (VIF) statistics were calculated (Table 7).

Table 7: Multicollinearity diagnostics

Variable	VIF	Tolerance
Digital advertising spending	3.41	0.293
Online consumers	3.76	0.266
Digital maturity index	2.98	0.335

Source: Author

Variance Inflation Factor (VIF) statistics were calculated to assess potential multicollinearity among predictors. All VIF values remain below the commonly accepted threshold of 5, suggesting that multicollinearity does not critically distort the regression estimates, although moderate correlations between predictors are present.

Based on the analysis of the data, a regression model was formed:

$$Y=1240.7 + 180.6X_1 + 11.2X_2 + 6850.4X_3 \quad (1)$$

Table 8 provides an interpretation and statistical description of the regression model parameters.

Table 8: Description of regression model parameters

Parameter	Coefficient β	Standard error	t-statistic	P-value
β_0 (constant)	1240.7	410.5	3.02	0.014
β_1 (advertising spend)	180.6	58.7	3.08	0.013
β_2 (online consumers)	11.2	3.5	3.20	0.011
β_3 (digital maturity)	6850.4	2050.8	3.34	0.009

$R^2 = 0.923$, Adjusted $R^2 = 0.911$, $F(3,16) = 61.24$, $p < 0.001$.
Source: Author

The macro-level regression model is based on a relatively small cross-country panel dataset (five countries observed over five years). Consequently, the statistical results should be interpreted cautiously as indicative relationships rather than definitive causal estimates. The analysis therefore serves primarily as an exploratory illustration of potential associations between digital marketing activity and export performance.

The estimated coefficients indicate a positive association between digital marketing inputs and export performance. However, given the aggregated,

country-level nature of the data and the limited number of observations, these coefficients should be interpreted as directional relationships rather than as precise marginal effects. The results suggest that higher levels of digital investment, broader online consumer engagement, and greater digital maturity are systematically associated with stronger export performance in agribusiness. The magnitude of the coefficients reflects scale differences between macroeconomic indicators and should not be interpreted as literal returns on investment at company level. All variables have $p < 0.05$, confirming their impact on the dependent variable. The high value of the F-test (61.24) indicates the significance of the model.

Table 9 provides a comparative analysis of the impact of agribusiness digitalization on exports.

Table 9: Comparative analysis of impact of digitalization on export of agricultural products

Country	Digital maturity level	Main digital platforms	Export growth (%)	Main growth factor	Export impact assessment
Ukraine	0.64	Facebook, Prom.ua, Rozetka, YouTube	+29.3	Targeted Ads, e-commerce integration	Medium. High online sales in the grain segment, but weak diversification
Slovakia	0.71	Allegro, Meta Ads, LinkedIn, Google Ads	+29.9	SEO, SMM tools, data analytics	High. Investments in SEO and advertising have led to increased exports of dairy and meat products
Germany	0.88	Amazon, Instagram, and corporate CRM systems	+33.1	CRM systems and Predictive Analytics	Very high. Advanced data analytics and online retail are contributing to sustained export growth
Italy	0.83	TikTok, Instagram, eBay	+35.5	Content marketing, branding	High. Emphasis on brand marketing and visual product identity

Kenya	0.52	WhatsApp Business, Facebook, Jumia	+37.7	Mobile advertising, social platforms	Moderate. Growth of mobile marketing, but limited by infrastructure

Source: Author

Countries with a higher digital maturity index have consistently higher export volumes, supporting the hypothesis of a positive impact of digital technologies. Although Kenya shows the highest growth rate in %, its absolute figures remain the lowest due to limited infrastructure. Germany and Italy showed the highest growth in export value, indicating effective use of digital maturity.

The Shapiro–Wilk test ($p = 0.31$) was used to test the normality of the distribution of residuals, which confirmed the normal distribution of errors. Heteroscedasticity was tested by the Broisch–Pagan test ($p = 0.44$), therefore, the variance of the residuals is constant.

Thus, digital investment is a key driver of international competitiveness. Digital advertising spending has a statistically significant impact on export volume ($\beta_1=180.6$, $p<0.05$). Engaging online consumers builds brand loyalty. In countries with a developed digital ecosystem (Germany, Italy), the correlation coefficient between the number of consumers and exports exceeds 0.9. The Digital Maturity Index is an integral indicator of the effectiveness of digitalization. It combines technological, organizational and analytical components that significantly increase the effectiveness of marketing strategies. Digital inequality remains a significant problem. In Kenya, limited access to high-speed Internet reduces the return on digital investments, despite the growth of online activity. European countries demonstrate convergence of models. Slovakia is gradually approaching the level of Italy thanks to investments in marketing analytics and programmatic advertising. Accordingly, for Ukraine, it is recommended to strengthen the analytical component of digital campaigns and expand the integration of e-commerce with export logistics platforms, for Kenya, to provide state subsidies for small and medium-sized enterprises (SMEs) in the field of digital marketing and training farmers, and for EU countries, to shift the emphasis from promotion to data analytics and artificial intelligence in demand forecasting.

For a deeper understanding of the practical aspects of integrating digital marketing tools into global agribusiness development processes, a comparative analysis of cases from five countries with different levels of digital maturity and structure of the agricultural sector was conducted: Ukraine, Slovakia, Germany, Italy and Kenya. The choice of these countries is justified by the need to reflect both the experience of EU countries with a high level of digitalization and that of the promising markets that are only transitioning to the digital economy. The methodological basis of the analysis was content analysis of open sources of official company websites, reports of FAO, OECD, Eurostat, industry publications and marketing analysts, as well as the case study method, which allows for the identification of the best practices in

implementing digital marketing. One representative company was selected for each country, namely Ukraine - MHP (Myronivsky Hliboproduct), Slovakia - Dan-Slovakia Agrar, a.s., Germany - Bayer Crop Science, Italy - Barilla Group (Agri-food division), Kenya - Twiga Foods.

To ensure analytical consistency across cases, the companies were examined using a common analytical framework consisting of four dimensions: the main digital marketing tools used; the level of integration of digital data into marketing decision-making; export market orientation and international reach; and key institutional or infrastructural constraints affecting digital strategy implementation. This framework allows for systematic comparison of digital marketing practices across different agribusiness environments.

Table 10 compares the implementation of digital marketing strategies in five companies located in different countries.

Table 10: Comparison of the application of digital marketing strategies in five companies from different countries

Country	Company	Main digital tools	Digitalization results	Challenges
Ukraine	MHP (Myronivsky Hliboproduct)	SMM tools, e-commerce, SEO, demand analytics	Growth in online sales, active promotion of brands through social networks	Limited infrastructure, low level of digital competence of farmers
Slovakia	Dan-Slovakia Agrar, a.s.	Content marketing, B2B platforms, targeted advertising	Increase in contracts, creation of an integrated digital catalogue	Competition with other agricultural brands
Germany	Bayer Crop Science	Big Data, AI, CRM systems, video marketing, mobile applications	Growth in market share in the EU, personalization of marketing through customer analytics	High costs for cybersecurity, regulatory restrictions
Italy	Barilla Group	Omnichannel strategy, social platforms, storytelling, influencer marketing	Increased consumer loyalty, export of products to a significant number of countries	Difficulty in coordinating digital campaigns across regions

Country	Company	Main digital tools	Digitalization results	Challenges
Kenya	Twiga Foods	Mobile marketing, WhatsApp Business, online marketplace, SMS advertising	Growth in income of small farmers, large number of active users of the application	Limited internet access, low financial inclusion

Source: Author

A comparative analysis of five agribusiness companies from countries with different levels of digital maturity illustrates how digital marketing tools support international market development. The cases include MHP (Ukraine), Dan-Slovakia Agrar (Slovakia), Bayer Crop Science (Germany), Barilla Group (Italy), and Twiga Foods (Kenya). These companies represent diverse institutional and technological environments and therefore provide insight into different models of digital marketing adoption in agribusiness.

The Ukrainian case (MHP) demonstrates the growing role of social media platforms, SEO tools, and data-driven marketing in promoting agricultural products and strengthening export competitiveness despite infrastructural constraints. In Slovakia, Dan-Slovakia Agrar focuses on content marketing, digital catalogues, and targeted advertising, illustrating how medium-sized agribusiness companies use digital communication to expand contracts and strengthen B2B relationships. Germany represents a highly developed digital ecosystem in agribusiness. Bayer Crop Science integrates artificial intelligence, big data analytics, and CRM systems into marketing strategies, enabling personalized communication with clients and more efficient market positioning. In Italy, Barilla Group employs an omnichannel strategy based on storytelling, brand identity, and social media engagement, demonstrating the importance of emotional branding in strengthening consumer trust and global brand recognition. The Kenyan case of Twiga Foods highlights the role of mobile-based digital marketing solutions in emerging economies. By combining mobile marketplaces, messaging platforms, and digital sales analytics, the company connects smallholder farmers with urban consumers and expands market access despite infrastructural limitations.

Thus, the level of digital maturity is directly correlated with the volume of exports: Germany and Italy demonstrate the highest indicators ($R^2 = 0.71$), while Ukraine and Kenya are average, due to infrastructure constraints. The main digital tools differ significantly by country. In EU countries, CRM systems, data analytics and omnichannel prevail; in developing countries, mobile services and social networks. Marketing effectiveness in developed countries is manifested through increased loyalty (Italy, Germany), while in countries with a lower level of digitalization - through increased income and expansion of markets (Kenya, Ukraine). The social effect of digital strategies is especially pronounced in Kenya, where technology has become a tool for financial inclusion. The European approach is characterized by systematicity,

integration of marketing with scientific research and high-quality data, while the Ukrainian model is more adaptive, with a focus on creativity and flexible communication channels.

A comparative analysis of companies from five countries shows that digital marketing tools are not only a tool for promotion, but also an element of strategic management of agribusiness. The most successful companies demonstrate the following patterns: integration of marketing and production data; focus on building long-term relationships with consumers; continuous training of personnel in digital skills; adaptation of content to the cultural characteristics of target markets. Therefore, the integration of digital marketing tools into the development of agribusiness contributes not only to economic growth, but also to strengthening the institutional capacity of the industry, creating the prerequisites for sustainable international development.

Across all cases, the effectiveness of digital marketing strategies appears to depend not only on technological adoption but also on the integration of digital data into strategic decision-making and the broader institutional environment in which agribusiness companies operate.

Given the cross-country nature of this study, the results were validated using a triangulation approach. The analysis compared different types of quantitative data (online surveys, export statistics, digital marketing investments) with qualitative evidence from company case studies. This approach reduced the risk of single-method bias and provided a more comprehensive understanding of the relationships between digitalization, marketing strategies, and export dynamics.

Triangulation covered three interrelated areas: methodological triangulation for comparing results obtained by different research methods (surveys, regression modelling, content analysis), source triangulation for comparing primary data (results of surveys of 495 consumers in five countries) with secondary statistical data, and analytical triangulation for independent verification of conclusions by comparing results for different countries and companies (MHP, Dan-Slovakia Agrar, a.s., Bayer Crop Science, Barilla Group, Twiga Foods).

Despite the high validity indicators, the study has several methodological and empirical limitations that affect the generalizability of the results. First, the macro-level dataset contains a relatively limited number of observations. The regression analysis is based on cross-country panel data covering five countries over the period 2020–2024. Consequently, the small sample size restricts the robustness of regression-based inference, and the results should therefore be interpreted primarily as exploratory evidence rather than as definitive causal estimates. Second, the development level of the digital infrastructure differs significantly across the countries included in the study. The level of internet coverage, digital literacy, and access to digital technologies varies considerably between national contexts. These differences may influence both the ability of consumers to participate in online surveys and the intensity of digital marketing channel usage. As a result, some indicators, such as the level of online trust or the frequency of digital purchases, may be underestimated in countries with a less developed digital infrastructure. Third, the time horizon of the study is relatively limited. The analysis covers

the period 2020–2024, which corresponds to a phase of accelerated digital transformation in agribusiness following the COVID-19 pandemic. However, this period may still be insufficient for capturing longer-term structural trends in digital marketing adoption and export dynamics. Fourth, the study may be affected by response subjectivity. Consumer surveys can be influenced by social desirability bias, whereby respondents tend to provide answers that they perceive as socially acceptable. Although the use of anonymous online questionnaires and standardized measurement scales helped reduce this risk, it cannot be eliminated. Fifth, the analysis is constrained by the limited availability of detailed financial data from smallholder farms. In several countries, particularly Ukraine and Kenya, many small agricultural producers do not publish financial reports, which complicates the quantitative evaluation of the effectiveness of digital marketing strategies at the micro level.

These limitations open several directions for future research. Further studies could employ larger cross-country datasets or company-level panel data to test the relationship between digital marketing investment and export performance more rigorously. Longitudinal analyses covering longer time periods would also help capture structural changes in agribusiness digitalization. In addition, future research may explore the role of artificial intelligence and advanced data analytics in digital marketing strategies, as well as behavioural mechanisms shaping consumer trust in digital agrifood markets.

Digital marketing tools are a strategic factor in the international competitiveness of agricultural enterprises. Their impact is positive but asymmetric, depending on the level of digital maturity, socio-cultural context and infrastructure. Consumer trust is becoming a central element of the effectiveness of digital strategies, and transparency, environmental friendliness and brand ethics are emerging as key values of the new marketing paradigm. Countries with a high level of digital integration demonstrate a higher return on investment in marketing, which should become a guideline for the transformational policy of developing countries. Further integration requires intersectoral cooperation, a combination of digital innovations, agricultural policy and educational programs. Digital marketing is not just a tool for promoting agricultural products, but a fundamental driver of structural changes in global agribusiness. Its implementation creates prerequisites for transparency, sustainability and integration into the global market, provided that digital inequality is overcome and institutional support is formed at the national and international levels.

6 Conclusions

The study of the integration of digital marketing tools into the processes of global agribusiness development allowed for a comprehensive assessment of how digitalization affects the competitiveness of the agricultural sector, the formation of consumer trust, export dynamics and the transformation of business models. The study demonstrates that, in the context of consumers' most recent online purchase of an agricultural product, digital interaction with a brand significantly shapes trust, satisfaction, digital loyalty, and repurchase intention. These perceptual mechanisms constitute the micro-foundation through which digital marketing contributes to international competitiveness

in agribusiness. The results confirmed the hypothesis that digital marketing acts as a strategic driver of the development of agricultural enterprises in the international dimension, ensuring transparency, enhancing communication efficiency and expanding market presence. The analysis conducted based on empirical and secondary statistical data showed that the use of digital technologies through social networks, e-commerce platforms, SEO, content marketing, and data analytics contributes to increasing customer loyalty, boosting sales and exports, as well as creating long-term competitive advantages.

The key conclusion is that digital marketing in agribusiness has ceased to be an auxiliary tool and has transformed into a strategic basis for global interaction between the producer, the consumer and the market. In modern conditions, it is the digital competence and digital maturity of enterprises that determine their ability to integrate into the global economy.

The conducted research confirmed the relevance of applying an interdisciplinary approach to the study of digital marketing in the agricultural sector. The results obtained are logically consistent with the following theoretical concepts: the theory of a resource-oriented approach (Barney, 1991) - digital technologies are considered as a strategic resource that is rare, valuable and difficult to copy by competitors. They create long-term advantages, forming a unique system of interaction with customers; the theory of diffusion of innovations (Rogers, 2003) - the speed of adaptation of digital marketing tools in different countries is determined by cultural, economic and technological barriers. The study confirmed that the level of the digital maturity of the agricultural sector directly and proportionally affects the effectiveness of marketing strategies; the concept of trust in the digital environment - trust is a key prerequisite for consumers to switch to online purchases of agricultural products. A high level of trust in brands is formed through transparency of information, openness of production processes, social and environmental responsibility of the enterprise; The UN Sustainable Development Model - digitalization of marketing contributes to inclusive economic growth, reduces transaction costs and optimizes resources, ensuring a sustainable chain of production and consumption. Thus, the results of the work not only confirm existing theoretical positions, but also expand them, by demonstrating that digital marketing in global agribusiness acts as a systemic factor in market transformation, combining innovation, trust and competitiveness.

Regression analysis indicates a positive association between digital marketing investment and export performance. However, given the aggregated country-level nature of the data and scale differences between the variables, the estimated coefficients should not be interpreted as precise marginal effects but rather as indicative directional relationships. The results suggest that higher levels of digital marketing investment, broader online consumer engagement, and greater digital maturity tend to be associated with stronger export performance in agribusiness.

A survey of 495 respondents in five countries revealed a direct relationship between the level of digital interaction with a brand and the level of trust in it. The highest indicators were observed in Germany and Italy, which indicates the established culture of consuming agricultural products through digital

channels. In Ukraine and Slovakia, a trend of gradual growth in trust was observed, which is due to the activation of local brands in social networks. Kenya, despite lower average indicators, demonstrates a rapid pace of development of mobile platforms, which are becoming a substitute for traditional marketing channels. It is proven that interaction in the digital space forms not only awareness, but also an emotional attachment of the consumer to the brand, which reduces the impact of price fluctuations and increases the frequency of repeat purchases.

A comparative analysis of five countries showed that the difference in the levels of digital maturity directly affects the effectiveness of the use of marketing tools. Germany and Italy demonstrate a high level of integration, which is manifested in the use of artificial intelligence (AI), Internet of Things (IoT) sensors, blockchain traceability systems and automated campaign management. Slovakia and Ukraine are characterized by an average level of development, with a focus on social networks, content marketing and online platforms. Kenya is at the initial stage of digital integration but is compensating for this gap thanks to mobile solutions (M-Farm, Twiga Foods) that simplify communication between farmers and buyers. These results indicate that the global digitalization of agribusiness is not homogeneous, and that the effectiveness of strategies is determined by a combination of infrastructural, educational and cultural factors.

From a practical point of view, it should be noted that digital marketing increases the efficiency of export activities. Companies that actively use digital channels often demonstrate faster expansion of export markets compared with companies relying primarily on traditional marketing channels. Successful brands use openness strategies: online production reports, video tours, and interactive maps of farms. This increases audience trust and loyalty. The use of big data, blockchain, and IoT allows you to track every stage of product movement, reduce losses, control quality, and reduce costs. Behavioural data analytics and targeting allow you to adapt content to the specifics of audiences in different countries, increasing advertising effectiveness and conversion rates. In Ukraine and Kenya, there is a need for digital marketing training programs for small producers, which will allow them to expand their participation in international supply chains. Government support in the form of grants, subsidies for digitalization, tax breaks, and educational initiatives is a crucial condition for the sustainable development of digital agrimarketing.

Despite the comprehensive nature of the analysis, there are certain limitations that affect the interpretation of the results. These limitations include uneven digital infrastructure across countries, the time frame of the study, the subjectivity of the surveys, the lack of detailed financial reports from small farms, and cultural differences.

Prospects for further research include modelling the impact of artificial intelligence on the effectiveness of digital strategies, studying the role of environmental, social, and governance (ESG) communication, expanding the sample, analysing long-term effects, behavioural modelling of consumers, and shaping digital inclusion policies.

The findings show that in the context of concrete online purchase episodes, trust, satisfaction, digital loyalty, and repurchase intention constitute the micro-foundations of digital marketing effectiveness in agribusiness. Digital marketing in global agribusiness performs not only the function of a communication tool, but also the role of a catalyst for market transformation, innovation and sustainable development. Its integration into strategic management allows enterprises to increase the effectiveness of communication with the target audience; optimize supply chains; increase the level of trust and transparency; strengthen positions in the international market. However, the key condition for realizing the potential of digital technologies is the balance between innovation and inclusiveness. Digital inequality, lack of infrastructure and limited competencies remain the main challenges that require systemic policies at the level of the state, international organizations and corporate associations.

Thus, the results of the study indicate that the integration of digital marketing tools into global agribusiness processes is not just a trend, but a necessary condition for its competitiveness, sustainability, and participation in the global knowledge economy.

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Digital Project Management Practices and the Economics of Hospitality Transformation: Evidence from Hotels and Apartments in the Adriatic Region

Original scientific paper

Luka Samaržija[1], Matia Torbarina[2], Nikolina Dukić Samaržija[3]

ABSTRACT

This paper investigates the use of project management practices in tourism accommodation facilities, comparing hotels and apartments in the Adriatic region of the Republic of Croatia. A structured questionnaire, based on an adapted list of practices, was distributed using online platforms, yielding 176 valid responses, of which 59.1% were from apartments and 40.9% from hotels. Descriptive statistics were used to profile respondents by demographic and job characteristics, while independent samples t-tests and effect size (Cohen's d) were applied to examine differences in the perceived usefulness and frequency of use of project management practices between the two groups. The results indicate that project activities are most often carried out only occasionally or rarely, and that owners and top/middle managers are most frequently responsible for project implementation, with formal project managers being present in a much smaller share of facilities. Statistically significant differences were identified between hotels and apartments for a limited number of practices, with hotels generally reporting a higher level of formalization and more frequent use of specific project management instruments, although effect sizes are mostly small to moderate. Overall, the findings suggest that project management in both hotels and apartments is still at a relatively low level of maturity, with apartments lagging behind hotels, and point to the need for greater formalization, training, and systematic use of project management methodologies to improve the effectiveness of project implementation in the tourism accommodation sector.

1 *PhD, Associate Professor, University of Rijeka, Faculty of Economics and Business, Ivana Filipovića 4, 51 000 Rijeka, Croatia. Phone_Number: +385 51 355 160. E-mail: luka.samarzija@efri.uniri.hr.*

2 *PhD, Assistant Professor, University of Rijeka, Faculty of Economics and Business, Ivana Filipovića 4, 51 000 Rijeka, Croatia. Phone_Number: +385 51 355 131. E-mail: matia.torbarina@efri.uniri.hr.*

3 *PhD, Associate Professor, University of Rijeka, Faculty of Economics and Business, Ivana Filipovića 4, 51 000 Rijeka, Croatia. Phone_Number: +385 51 355 141. E-mail: nikolina.dukic.samarzija@efri.uniri.hr.*

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1 Introduction

Tourism is the most important economic sector in the Republic of Croatia, especially during the summer months. According to data from the Croatian Bureau of Statistics, from January to August 2024, there were 14.67 million arrivals of foreign tourists and 2.20 million arrivals of domestic tourists (HTZ, 2024). Tourism also benefits other sectors, such as the food and construction industries as well as hospitality, with hospitality benefitting the most due to significant investments in various categories of accommodation capacities. According to data from 2023, private rooms and apartments make up 62.3% of accommodation capacities, campsites and camping grounds 20.9%, and hotels only 10% (HTZ, 2024).

In modern hospitality, marked by a dynamic market, growing guest expectations, and strong competition, applying project management practices has become key to successfully managing and developing hospitality facilities. Hospitality projects encompass a wide range of activities—from construction, renovation, and technological innovation to the introduction of new services and products, marketing campaigns, and the optimization of operational processes. Due to the complexity and diversity of projects, managers are increasingly introducing modern project management practices to enhance efficiency, reduce risks, and improve guest satisfaction.

Over recent decades, the hospitality industry has evolved from traditional management approaches to integrating advanced digital technologies such as Agile, Scrum, and hybrid project management models, reflecting a shift toward more adaptive and efficient project execution (Bezruchenkov, 2023). This evolution is significant given the sector's substantial economic contribution and the growing demand for skilled professionals capable of leveraging project management tools to enhance operational efficiency and service quality (Deri & Ragavan, 2023). In today's business environment, the hospitality industry faces numerous challenges, such as increasing competition, changing guest needs, and the constant demand for innovation and optimization of business processes. For these reasons, effective project management has become crucial for achieving sustainable development and gaining a competitive advantage. Today, project management tools are primarily integrated into software programs and are used for planning, organizing, monitoring, and reporting within hospitality establishments, enabling better resource management, improved cost control, and the timely completion of tasks. Additionally, the appropriate selection of project success indicators forms the foundation for future planning of development needs in hospitality facilities. The application of project management tools and indicators in hospitality not only facilitates the initiation of new projects (products and services), but also improves team coordination, reduces the risk of market launch delays,

and ultimately contributes to greater guest satisfaction. However, the level of implementation and the effectiveness of these tools and indicators differ depending on the type of accommodation facility, available resources, and organizational culture.

The aim of this research is to identify and analyse the ways in which project management practices (tools and success indicators) are used in different types of accommodation categories. The paper presents a comparative analysis of hotel and apartment accommodations in the Adriatic region of the Republic of Croatia. The difference in project management implementation between hotels and apartments arises from the varying complexity of business systems, internal processes, service structure, and defined business objectives. A hotel is an organizationally more complex system with multiple departments (front desk, restaurants, technical service), requiring detailed project planning, coordination of different teams, and specific quality standards and procedures integrated into various aspects of operations (safety and day-to-day management). An apartment as a type of accommodation usually refers to a single or smaller number of units, so project management is simpler, more decentralized, and mostly focused on operational tasks like furnishing, running, or maintaining the property. Hotel projects are characterized by a larger number of participants and stricter regulations, while projects in apartments are more individualized and flexible, involving lower risk and less complexity in execution.

Despite the growing interest in project management in the hospitality industry, significant gaps remain in understanding how project management practices differ across types of accommodation facilities and the contexts in which these facilities operate. The emerging literature predominantly focuses on digital transformation and technology adoption in hotels (Buhalis et al., 2023; Chourasia, 2025), with limited attention paid to systematic comparisons between different accommodation segments. While studies theoretically examine project management systems (Bezruchenkov, 2023; Turginbayeva et al., 2020) or explore agile methodologies in non-technological contexts (Almeida, 2021), empirical validation of specific project management practices remains scarce. In particular, Chalupa and Petriček. (2020) identified the lack of empirical data in hospitality project management research as a critical limitation.

The absence of comparative studies between hotels and apartments represents a particularly pronounced gap. Existing research typically treats hospitality as homogeneous (Mehrotra et al., 2025) or focuses exclusively on specific segments such as luxury hotels (Hint et al., 2022) or budget accommodations, without cross-segment analysis. Furthermore, most empirical studies remain geographically isolated, Bulgaria (Strankova & Kaleychev, 2023), the Czech Republic (Chalupa & Petriček, 2020), Romania (Hint et al., 2022), limiting the understanding of regional variations in PM formalization and practices adoption. This paper addresses these gaps by providing the first systematic comparison of PM practices between hotels and apartments within a unified regional context by empirically examining formalization levels, specific tools usage (progress meetings, PM software, quality control mechanisms), and risk management approaches. However, broader international comparative

studies and longitudinal investigations of PM practice evolution remain necessary to advance the theoretical understanding and practical application across diverse hospitality contexts.

Scientific literature (Poulova et. al., 2022., Mitchell, 2024., Song et.al., 2024) highlights that successful application of project management tools in the hotel industry is linked to clearly defined project goals, efficient resource management, continuous progress monitoring, and timely risk management. Special attention is paid to maintaining the quality of the guest experience during project implementation, for example, through real-time guest satisfaction tracking systems or by appointing staff responsible for monitoring the impact of projects on everyday operations. In conclusion, the use of project management practices in hospitality facilities enables greater operational efficiency, better resource utilization, and increased competitiveness on the market through innovation and higher-quality services.

Specialized software solutions that integrate a large number of project management practices enable structured planning, monitoring, and control of activities, resources and budgets. The main tools provide various functionalities such as distributing tasks, defining responsibilities, setting deadlines, tracking progress, and generating automatic reports, thereby facilitating team coordination, increasing transparency, and enabling timely decision-making. Implementing digital project management platforms is especially important in hospitality, where maintaining a high level of operational excellence with minimal disruption to guests is essential. In addition, communication tools and collaboration platforms, such as messaging apps and video conferencing solutions, ensure effective information exchange and teamwork, which is crucial for the success of projects in the hotel sector. Based on all of the above, a research question was formed: How do hotels and apartments in the Adriatic region of the Republic of Croatia differ in the use and implementation of project management practices, including tools and success indicators?

This research provides one of the first empirical, survey-based comparisons of project management practices between hotels and apartments within the same tourism region, with a focus on the Adriatic coast of the Republic of Croatia, where private apartments dominate total accommodation capacity but remain underexplored in PM literature. It extends existing project management studies by operationalizing a comprehensive list of tools and success indicators in a hospitality context and quantitatively testing their perceived usefulness and frequency of use across two structurally different accommodation types. By identifying the overall low maturity level of project management and revealing specific areas where apartments lag behind hotels (formalization, use of software tools, structured monitoring and control), the study generates context-specific evidence that can inform targeted training, digitalization, and policy measures aimed at improving project implementation in the Croatian tourism accommodation sector.

2 Literature review

Project management practices include tools and indicators that help in planning, organizing, monitoring and controlling projects. Their purpose is to facilitate the management of tasks, deadlines, resources and budget, and to increase the efficiency and effectiveness of the project team and ultimately the project itself.

A mixed-methods research strategy was utilized by Fernandes et al. (2013) in order to discover the practitioners' perspectives of the most successful project management methodologies for the purpose of improving project management performance. Initial research consisted of conducting semi-structured interviews and qualitative data analysis in order to examine and identify the project management tools and practices that were deemed to be the most effective across a variety of organizational situations. Additionally, in order to corroborate or reject the findings that were obtained from the interviews, a survey questionnaire was issued to a wider variety of respondents in order to obtain their perspectives. Practitioners from all over the world were asked to fill out the questionnaires systematically. According to the findings, the top 20 tools and approaches identified are composed of instruments that are widely recognized and applied.

Table 1: Most commonly used project management tools in 2013

1	Progress report	11	Gantt chart
2	Requirements analysis	12	Activity list
3	Progress meetings	13	Client acceptance form
4	Risk identification	14	Risk response plan / Contingent plans
5	Project scope statement	15	Project statement of work
6	Kick-off meeting	16	Communication plan
7	Milestone planning	17	Responsibility assignment matrix
8	Work breakdown structure	18	Baseline plan
9	Change request	19	Qualitative risk analysis
10	Project issue log	20	Project charter

Source: Fernandes et al. 2013

The most common approaches to project management have been identified through specific empirical studies, as demonstrated by the research carried out by Besner and Hobbs (2006) and Patanakul et al. (2010). White and Fortune (2002) conducted a survey with the purpose of determining the extent to which project managers make use of the various approaches that are available and assessing the effectiveness of these methods. An inventory of tools, techniques, and indicators was provided by the authors, and respondents

were asked to describe which of these had been applied in the project that was being evaluated for the purpose of the survey. According to Kerzner (2013), the survey options were created from a compendium of standard textbooks on project management. According to the findings of White and Fortune, the tools that were utilized the most frequently were software (used by 77% of respondents), Gantt charts (used by 64%), and cost–benefit analysis (used by 37%).

A questionnaire study conducted by Besner and Hobbs in 2006, revealed that the utilization levels of numerous tools and methods, measured on a scale from 1 (not employed) to 5 (very extensive use), exhibited significant variability, ranging from 1.4 to 4.1. Besner and Hobbs (2006) concur with the conclusions reached by White and Fortune (2002). Although Besner and Hobbs selected a larger array of tools and procedures, the three most commonly employed, as identified by White and Fortune (2002), also rank first on the list provided by Besner and Hobbs (2006). In 2012, Besner and Hobbs (2012a) undertook a supplementary study with two main objectives: firstly, to illustrate that practitioners employ project management tools and indicators in groups, referred to as "toolsets," and secondly, to investigate the application of these "toolsets" across various project types. The research findings revealed that the management of four separate project types—construction, service, information technology and telecommunications, and software development—differs. According to Besner and Hobbs (2006), a summary of the most frequently used project management approaches across several industries is provided in Appendix A (Table A1).

Studies have been conducted in various countries and sectors with the aim of determining which project management practices are actually used most frequently in different organizations. It was found that some practices are used more often than others (Crispim, Silva & Rego, 2019; Tereso et al., 2019). After carrying out quantitative research, it was established that the most frequently used practices are related to communication or planning (Fernandes, Ward, & Araújo, 2013; Tereso et al., 2019). Furthermore, a qualitative study conducted by Fernandes and David O'Sullivan in 2022, showed that communication-oriented practices received the highest ratings from practitioners. Detailed research results are presented in Table A1 in the Appendix.

Recent literature reveals that digital transformation has fundamentally reshaped the PM tools landscape while maintaining the relevance of traditional tools in evolved forms. Traditional tools documented by Besner and Hobbs remain foundational but are now delivered through sophisticated digital platforms. Radujković and Sjekavica (2021) found that Gantt charts, WBS, and milestone planning continue to be widely used by engineering project managers, although implemented digitally rather than on paper. Anjum et al. (2025) note that these traditional tools serve as foundational elements within modern AI-driven PM systems, providing a structure that can be optimized by algorithms. Miah (2025) confirms that contemporary PM software universally includes digital versions of traditional tools alongside newer features like real-time dashboards and automated reporting.

The most significant evolution involves the emergence of AI-powered tools and cloud-based collaboration platforms. Anjum et al. (2025) and Reznikov

(2025) document AI applications in predictive scheduling, risk forecasting, and automated decision support capabilities absent from traditional project management software. Pawłowski and Plechawska (2022) demonstrate how modern platforms (example: Asana, Trello and Wrike) integrate multiple PM functions into unified digital ecosystems, as opposed to the siloed tools of 2006. Kılıç and Gurcanli (2025) illustrate how Jira, Confluence, and Trello enable real-time collaboration across distributed teams, while Ershadi et al. (2021) show how synchronous communication tools have supplemented periodic progress meetings.

Methodological shifts have driven tool evolution, tracing the "journey from traditional to agile" enabled by digital platforms. Haddab (2024) demonstrates that hybrid PM models now seamlessly integrate traditional structured planning tools with adaptive execution mechanisms through digital platforms. This evolution suggests that while Besner and Hobbs' core tools remain relevant, their implementation and capabilities have been dramatically enhanced by digital transformation, AI integration, and cloud-based collaboration technologies.

The key indicators of project management represent measurable criteria that are used to monitor the progress and success of the project in relation to the set goals (Ogunlana & Toor, 2010). They enable project managers and organizations to quantitatively and qualitatively evaluate project results and identify areas for improvement in a timely manner. The achievement of these main categories in the planned sizes entails some other consequences, thus increasing the degree of achieved efficiency and effectiveness of the project objectives, and increasing the likelihood of achieving the project's vision, mission and strategy (Cetinski & Perić, 2013).

The most important indicators of project management success – quality, cost, time and ROI have been thoroughly researched in the literature. The most famous author in this field is Harold Kerzner (2013), who systematically addresses the measurement and monitoring of these KPIs in his books and manuals. The Project Management Institute (PMI, 2021) also defines time, cost, quality and return on investment as key metrics for assessing project success through the PMBOK standards. Scientific works, such as those by Siva Kumar (2020) and Albuoul (2017), confirm that these indicators are universal and applicable in different industries. Professional articles and guides (e.g. Westland, 2007) emphasize the practical importance of continuously monitoring these measures for timely decision-making and successful project management. Overall, quality, cost, time and ROI form the basis of systematic management and evaluation of project success according to contemporary literature.

3 Methodology

The methodology used in this paper is a quantitative survey-based approach. Specifically, the research employed a questionnaire distributed to managers of hotels and apartments in the Adriatic region, collecting demographic data as well as information on project management practices and frequency of use. Respondents rated the frequency of each practice on a Likert scale (1–5), and

the data were analysed using descriptive statistics, comparative statistical analyses (mean, t-test, p-values, Cohen's d), and cluster analysis to compare how project management practices (tools and indicators) are implemented in hotels and apartment businesses.

3.1 Questionnaire design

In order to determine the purpose of the research, a questionnaire was first created and distributed. The first part of the questionnaire was used to collect information about the respondent, such as gender, age, level of education, type of facility in which she or he works, period of time in which he or she is employed and what is his or her position in the accommodation facility. The second part of the questionnaire collected information on the frequency of project activities, the competence of persons involved in project implementation, the time commitment for project implementation and the roles that individuals have in implementing project activities. The last, third part of the questionnaire collected information on the tools used and indicators of project management in hotels and apartments. The selection of tested tools and indicators resulted from a cross-check of papers and studies published by various authors, including Besner and Hobbs (2006); Fernandes et al. (2013); Papke-Shields et al. (2010); and Sensini et al (2021). However, the work that had the greatest influence on the selection was that of Besner and Hobbs (2006). In the aforementioned research, 70 most commonly used project management tools were tested in the information and communication sector, manufacturing, construction and service sectors. In the pilot study, five hotel managers and five apartment managers participated, who identified 20 project management tools most commonly used in the implementation of projects in the hospitality industry. In addition to the tools, the most common indicators of the success of the application of project management tools were also tested, namely, time, cost, quality and financial return (ROI).

Table 2: Project management practices covered by the research

Project management practices	Project management tools	Project selection method
		Kick off meeting
		Project charter
		Risk management
		Budgeting
		Project scope statement
		Activity list
		Project management software
		Work breakdown structure (WBS)
		Organizational breakdown structure (OBS)
		Gantt chart
		Change request
		Progress report
		Progress meetings
		Customer satisfaction surveys
		Cost-benefit analysis
		Quality inspection
		Database of contracts data
		Project takeover documentation
		Cost database
	Project management key performance indicators	Cost
		Time
		Quality
		ROI

Source: Authors

Respondents were asked to rate the frequency of usage for each tool and indicator in the section of the questionnaire that was devoted to project management tools and indicators. The scale ranged from 1 to 5, with 1 indicating “never used,” 2 indicating “rarely used,” 3 indicating “occasionally used,” 4 indicating “often used,” and 5 implying “always used.” Data were collected to facilitate the categorization of the sample and to carry out an investigation into the discrepancies that exist among the various types of accommodations. In addition, a number of interactions were evaluated in order to determine the characteristics that influence the utilization of project management tools. These characteristics include the respondent’s position, age, gender, and educational attainment. In the field of project management, it was predicted that persons who had a greater number of years of experience or a higher educational attainment would apply project management tactics

more frequently during the course of their work.

The survey was conducted in the period from June 1, 2024 to August 1, 2024. The surveys were sent to 150 addresses, and a total of 72 properly completed surveys were received, resulting in a response rate of 48%. Since the collected sample was small, the research was extended to include apartments owned by legal entities, provided that each entity managed at least five apartments, as a higher number of units is expected to result in a greater application of project management practices. The number of apartments that were contacted to participate in this survey was 200, and 104 correctly completed responses were received. Hotel personnel completed the questionnaires via the online network service SurveyMonkeyTM, and the questionnaires were sent by email with a description explaining the objectives of the survey. The questionnaires were distributed to respondents working in apartments via the Airbnb communication platform, while contacts for hotels were obtained via the booking.com portal and a direct internet search. Respondents who did not complete the questionnaires in the first round of sending, received a reminder to participate in the study again after three weeks, with an online link to the questionnaires and a request to complete them.

In order to evaluate the usefulness, comprehensibility, length, and clarity of the questionnaire, a preliminary test was carried out prior to its distribution across the population. According to Wideman (2002), the questionnaire that was built specifically for the purpose of providing succinct descriptions of each tool and method made use of jQuery UI Tooltip. A convenience sample was used for the purpose of carrying out this test. During the examination, both comprehension and the amount of time needed to finish the questionnaire were taken into consideration. There were just a few minor changes that needed to be made before the final version of the questionnaire could be sent. These changes were made with the intention to remove any ambiguities and to improve the layout in order to make it more readable. Following the completion of those revisions, the questionnaire was sent through a variety of different communication channels.

4 Research results and discussion

4.1 Research results

Descriptive statistical analysis is a set of methods by which collected data is organized, summarized and described in order to clearly present the basic characteristics of the data set. The data from the first part of the questionnaire were summarized in a way that was as clear as possible and that best described the collected data. Thus, the collected data were grouped according to the following criteria: age, gender, level of education, type of facility in which the respondents work, time period of employment, position in the facility, frequency of project activities, education acquired in the field of activities and project management, and the role of the respondent in project implementation activities. Based on the participant data, a descriptive analysis can be made to show the basic characteristics of the respondents, which is presented in Table 3.

Table 3: Descriptive research

Variables	Levels	N	%
Gender	Male	80	45.5%
	Female	97	54.5%
Age	18-24	4	2.3%
	25-34	54	30.7%
	35-44	112	63.1%
	45-54	7	4%
Education level	Doctoral studies / master of science	5	2.8%
	Secondary school	100	56.8%
	Graduate	52	29.5%
	Undergraduate	19	10.8%
Type of facility you work in	Apartment	104	59.1%
	Hotel	72	40.9%
How long have you been working in your current facility?	11-20 years	18	10.2%
	5-10 years	92	52.3%
	Less than 5 years	66	37,5%
What is your position in the facility?	Administrative and accounting worker	14	8%
	Top-level manager	21	11.9%
	Lower-level manager	90	51.1%
	Mid-level manager	16	9.1%
	Other hotel staff (receptionist, waiter, cook, guard, etc.)	35	19.9%
How often do you carry out project activities?	Never	2	1.1%
	Occasionally	80	45.5%
	Rarely	80	45.5%
	Very often	1	0.6%
	Frequently	13	7.4%
Who is responsible for project implementation in your facility?	Top and middle-level manager	46	26.1%
	Lower-level manager	13	7.4%
	No one is involved in project implementation	2	1.1%
	Project manager who is responsible for project management	24	13.6%
	External collaborators	7	4%
	Owner	84	47.7%

Education acquired in the field of project activities and management?	Master's Degree/MBA Degree	5	2.8%
	Secondary school	70	39.5%
	Project Management Course	4	2.3%
	Project Management Courses	30	14.7%
	Graduate level	56	31.6%
	Undergraduate level	15	9%
What is your role in project implementation activities?	Administration and Accounting	31	17.5%
	Project Manager	15	8.5%
	Project Manager	38	21.5%
	Member of the Core Project Team	92	52.5%

Source: Authors

The majority of the surveyed participants are women (54.5%), while men make up 45.5% of the respondents. The largest share of participants is in the age group 35-44 years old (63.1%), followed by those aged 25-34 (30.7%). Other age groups are significantly less represented. The analysis of the level of education shows that most participants have completed secondary education (56.8%), while 29.5% hold a graduate degree, and 10.8% hold a bachelor's degree, and 2.8% of the respondents have a master's or doctorate degree. The majority of the respondents work in apartments (59.1%), while 40.9% work in hotels. The analysis of project activities found that they are most often carried out occasionally or rarely (45.5% each), while only 7.4% are carried out often, and very often, only 0.6%. When examining the responsibilities for project initiation, it was determined that it is most often initiated by facility owners (47.7%), followed by top and middle level managers (26.1%), while project managers account for 13.6%. The surveyed participants are most often members of the narrow project team (52.5%), project managers (21.5%) or members of the administration (17.5%). These results indicate a diverse, but dominantly medium-educated and management-oriented population of employees in tourist facilities, with an emphasis on apartment accommodation and significant involvement of owners in project management. Table 4 shows a comparative statistical analysis of the project management practices in hotels and apartments.

Next, the study continued with the analysis of the mean, t-test, p-value, and Cohen's d indicator. The mean is the average of a data set and indicates a typical value in that set. The t-test is a statistical test used to compare the mean values of two groups and determine whether there is a significant difference between them. The p-value indicates the probability that the observed difference between the groups occurred by chance; if the p-value is less than 0.05, the difference is considered statistically significant. Finally, the Cohen's d indicator is a measure of effect size that indicates how large the difference between the groups is in relation to the variability of the data.

Table 4: Comparative analysis of project management practices

Label	Object type	Mean	SD	T	P	d
Project selection method	Hotel	1,51	0,75	0.392	0.6953	0.061
Project selection method	Apartment	1,56	0,69			
Kick off meeting	Hotel	3	1,21	-9.382	p < 0.001	-1.64
Kick off meeting	Apartment	1,59	0,49			
Project charter	Hotel	1,83	1,05	-0.107	0.9147	-0.017
Project charter	Apartment	1,82	0,86			
Customer satisfaction surveys	Hotel	4,12	0,67	-13.028	p < 0.001	-1.856
Customer satisfaction surveys	Apartment	2,46	1,02			
Project management software for task scheduling	Hotel	4,19	0,62	-36.561	p < 0.001	-6.072
Project management software for task scheduling	Apartment	1,18	0,39			
Quality inspection	Hotel	3,78	1,02	-10.625	p < 0.001	-1.704
Quality inspection	Apartment	2,25	0,8			
Time	Hotel	3,69	0,82	-12.306	p < 0.001	-1.933
Time	Apartment	2,23	0,71			
Cost	Hotel	3,81	0,83	-7.147	p < 0.001	-1.082
Cost	Apartment	2,87	0,89			
Quality	Hotel	3,15	1,32	-5.11	p < 0.001	-0.863
Quality	Apartment	2,28	0,73			
ROI	Hotel	3,85	0,91	-8.907	p < 0.001	-1.441
ROI	Apartment	2,72	0,67			

Label	Object type	Mean	SD	T	P	d
WBS	Hotel	1,32	0,58	-4.152	p < 0.001	-0.744
WBS	Apartment	1,03	0,17			
OBS	Hotel	1,26	0,75	-2.734	0.0078	-0.498
OBS	Apartment	1,02	0,14			
Gantt chart	Hotel	1,89	0,88	-2.251	0.0262	-0.365
Gantt chart	Apartment	1,62	0,64			
Risk management	Hotel	1,81	0,94	3.15	0.002	0.484
Risk management	Apartment	2,26	0,93			
Budgeting	Hotel	3,53	1,32	-6.389	p < 0.001	-1
Budgeting	Apartment	2,29	1,18			
Project scope statement	Hotel	2,11	1	-9.088	p < 0.001	-1.659
Project scope statement	Apartment	1,03	0,17			
Activity list	Hotel	2,79	1,09	-5.27	p < 0.001	-0.853
Activity list	Apartment	2	0,8			
CBA analysis	Hotel	2,81	1,55	-4.934	p < 0.001	-0.851
CBA analysis	Apartment	1,84	0,73			
Change request	Hotel	3,56	0,92	-15.276	p < 0.001	-2.486
Change request	Apartment	1,63	0,65			
Progress report	Hotel	3,69	0,76	-29.439	p < 0.001	-5.367
Progress report	Apartment	1,02	0,14			
Progress meetings	Hotel	3,81	0,78	-23.335	p < 0.001	-3.876
Progress meetings	Apartment	1,38	0,49			
Cost database	Hotel	3,86	0,88	-22.73	p < 0.001	-3.869
Cost database	Apartment	1,3	0,46			

Label	Object type	Mean	SD	T	P	d
Database of contracts data	Hotel	3,01	1	-5.821	p < 0.001	-0.951
Database of contracts data	Apartment	2,22	0,7			
Project takeover documentation	Hotel	2,4	1,13	-2.214	0.0289	-0.366
Project takeover documentation	Apartment	2,07	0,73			

Source: Authors

The results of the comparative analysis for individual project management tool indicate the following:

1. Project selection method. There is no significant difference in the use of project selection methods between hotels and apartments. Both types of facilities use these methods to a similar extent, indicating a uniform approach in this phase of project management. (Hotel: average 1.51 (SD 0.75), Apartment: average 1.56 (SD 0.69) and t = 0.392, p = 0.6953, d = 0.061
2. Kick off meeting. Hotels hold kick off meetings significantly more often than apartments. The large effect size (d = -1.64) indicates a strong difference, which may mean that hotels attach greater importance to the formal start of the project. (Hotel: 3.00 (SD 1.21), Apartment: 1.59 (SD 0.49) and t = -9.382, p < 0.001, d = -1.64).
3. Project charter. There is no difference in the use of the project charter between hotels and apartments. This document is probably used equally rarely or equally often in both types of facilities. (Hotel: 1.83 (SD 1.05), Apartment: 1.82 (SD 0.86) and t = -0.107, p = 0.9147, d = -0.017).
4. Customer satisfaction surveys. Hotels conduct customer satisfaction surveys significantly more often. The big difference can be due to the hotel's greater focus on service quality and guest feedback. (Hotel: 4.12 (SD 0.67), Apartment: 2.46 (SD 1.02) and t = -13.028, p < 0.001, d = -1.856).
5. Project management software for task scheduling. This is the biggest difference in the table. Hotels almost regularly monitor the success of the project with software tools, while this practice is almost negligible in apartments. A large Cohen's d indicates a very strong difference in approach to project management. (Hotel: 4.19 (SD 0.62), Apartment: 1.18 (SD 0.39) and t = -36.561, p < 0.001, d = -6.072).
6. Quality inspection. Hotels conduct quality inspections more often, which is expected given the greater focus on standardization and quality control. (Hotel: 3.78 (SD 1.02), Apartment: 2.25 (SD 0.80) and t = -10.625, p < 0.001, d = -1.704).

7. Time, cost, quality and ROI. Hotels are more systematic in monitoring and managing these key aspects of projects, while apartments have lower scores, which may indicate a less formalized approach or fewer management resources. For all key parameters, hotels have significantly higher scores (time: 3.69 vs. 2.23; costs: 3.81 vs. 2.87; quality: 3.15 vs. 2.28; financial return: 3.85 vs. 2.72).
8. WBS (Work Breakdown Structure) and OBS (Project Organizational Structure). Hotels are more likely to use structured methods of project planning and organization. Hotels have slightly higher scores in the use of WBS and OBS, with small to medium effects (d = -0.744 and -0.498).
9. Gantt chart. Hotels use Gantt charts more often, but the difference is smaller compared to other elements (Hotel: 1.89, Apartment: 1.62, t = -2.251, p = 0.0262, d = -0.365).
10. Risk management. The only element where apartments are rated higher than hotels. This may mean that apartments pay more attention to risk identification or are more aware of risks in their projects. (Hotel: 1.81, Apartment: 2.26, t = 3.15, p = 0.002, d = 0.484).
11. Budgeting, project scope statement, CBA analysis. Hotels carry out detailed planning and analyses of costs and activities in their projects. Hotels have significantly higher ratings in all these elements, with large effects (d from -0.851 to -1.659).
12. Change request, progress report, progress meetings, cost database. Progress report and change request is significantly more developed in hotels (d from -2,486 to -5,367), which may indicate more formal and systematic project management.
13. Database of contracts data and project takeover documentation. Formalities related to project completion and takeover are more frequent and better developed in hotels. Hotels have higher ratings, but the differences are smaller compared to other elements. The aforementioned results from the fact that the project takeover documentation has the smallest effect size (d = -0.366), but it is still statistically significant.

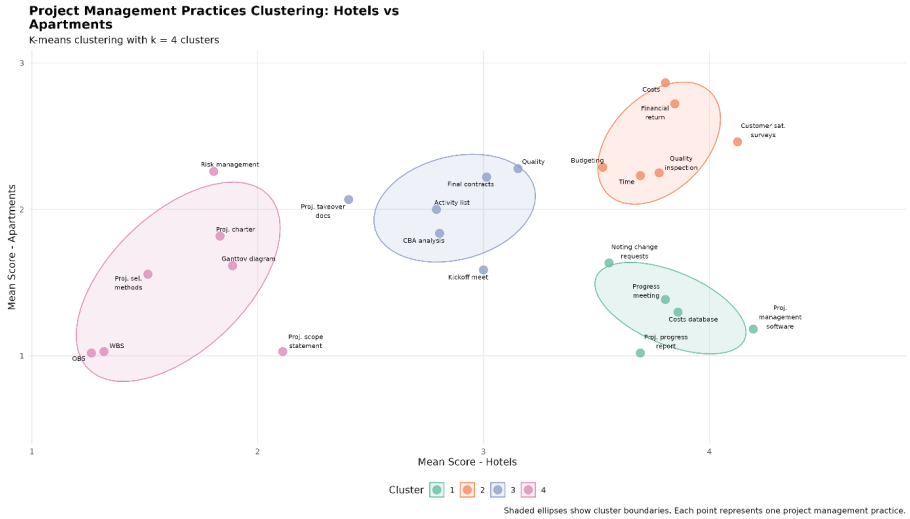
Hotels show significantly greater application, formalization and systematicity in project management in almost all areas analysed. Apartments are less formal, with lower scores in most elements, except for risk management where they are rated slightly higher. The differences are often very large, indicating different approaches and levels of maturity in project management practices between these two types of facilities. The analysis continues with a comparative analysis of the mean values presented in Figure 1.

In the last step, cluster analysis was performed to group the observed tools and indicators into homogeneous groups based on their mutual similarity or connection. The goal is to make members of the same group as similar to each other as possible, and as different as possible from members of other groups. This method is often used in combination with other multivariate analyses to identify natural groups within the data and better understand their structure

(Puška & Beganović, 2016).

The presented cluster analysis of business practices in hotels and apartments provides a detailed insight into the way in which individual practices are applied and evaluated in these two accommodation sectors. The analysis was conducted using the K-means method with four clusters, where each point on the graph represents one business practice, and its position is determined by the average usage ratings in hotels (x-axis) and apartments (y-axis). The clusters are shown in different colours and include practices that are similar in the way and frequency of application.

Figure 1: Cluster analysis



Source: Authors

Cluster 1, marked in green, includes the following practices: change requests, progress meetings, costs database, progress report and project management software for task scheduling. These practices have high ratings in hotels, but lower in apartments. They are predominantly related to formalized processes of monitoring, reporting and change management. This leads to the conclusion that hotels pay more attention to these practices, which may be the result of greater complexity and regulation of hotel business.

Cluster 2 is marked with an orange ellipse and contains the following practices: costs, ROI, quality inspection, time, budgeting, customer satisfaction surveys. The aforementioned practices were rated highly in both sectors, with a slight advantage in apartments, which means that apartments attach more importance to guest feedback and financial indicators, which indicates market orientation and the need for cost optimization.

Cluster 3 is marked in purple and includes the following practices: OBS, WBS, project selection methods, risk management, project charter, Gantt diagram

and project scope statement. This cluster is marked by slightly lower scores in both sectors, but is still somewhat more pronounced in apartments, probably due to the need for basic structure and planning in smaller business systems. These practices are related to methodology and project planning.

Cluster 4 is shown as a blue ellipse and includes database of contracts data, activity list, CBA analysis, kickoff meeting, quality, project takeover documentation. These practices are fundamental to project management and have been used in both sectors, indicating their universal value.

The conclusion of the cluster analysis is that hotels value formalized and structured processes more, which is evident from cluster 1. Apartments are more oriented towards financial indicators and guest satisfaction (cluster 2). There are practices that are less important in both sectors, but somewhat more so in apartments (cluster 3). Some practices are universally important and are used in both sectors (cluster 4). This cluster analysis enables management to recognize the differences and similarities in business practices between hotels and apartments, and to adapt or improve certain practices according to the specifics of the sector. In this way, better results and a competitive advantage can be achieved.

4.2 Discussion

The findings confirm that project management practices in Croatian hospitality remain only partially formalized, with a clear gap between hotels and apartments in the breadth and depth of tools used. This aligns with previous studies showing that communication and planning related tools are most common, while more sophisticated methods remain underutilized in many service sectors. The dominance of tools such as progress reports, progress meetings, Gantt charts, and customer satisfaction surveys in hotels is consistent with international evidence that communication and planning instruments are among the most frequently applied project management practices in organizations. Studies by White and Fortune (2002), Besner and Hobbs (2006, 2012), Fernandes et al. (2013) and Tereso et al. (2019) similarly show that software support, Gantt charts, cost–benefit analysis and communication-focused tools form the core “toolset” across multiple industries, which is echoed in this sample of hotels.

In this research, hotels report significantly higher use of progress meetings, project management software, cost databases and quality inspection mechanisms, which suggests a more structured and systematized approach to projects that mirrors the “toolset clusters” identified by Besner and Hobbs in more complex project environments such as construction, ICT and services. At the same time, the comparatively low levels of WBS, OBS and project charter usage in both hotels and apartments indicate that many hospitality projects still rely on partial or ad hoc applications of project management methodologies, confirming earlier observations that formal techniques are less embedded in service organizations than in engineering-based sectors.

The strong, statistically significant differences in the use of customer satisfaction surveys, project management software and change request procedures between hotels and apartments support the literature that links higher

organizational complexity with greater formalization of project management. Hotels in this study exhibit patterns consistent with prior findings that larger, multi-departmental service organizations tend to adopt more structured methods and digital tools to manage interdepartmental coordination, quality standards and guest experience.

Apartments, by contrast, rely on simpler, more flexible approaches and show lower mean values for most tools and KPIs, which corresponds to the predominantly small-scale, owner-managed nature of this segment highlighted in hospitality studies that treat smaller properties as less formalized and more intuitive in their management style. The fact that owners and lower-level managers are the primary drivers of project implementation in apartments further illustrates this informality and supports the notion that project management in micro and small tourism enterprises is frequently embedded in everyday operations rather than structured as separate project governance. A particularly interesting finding is that apartments score higher than hotels on risk management, contrary to the general pattern of lower formalization. This result resonates with recent research emphasizing the vulnerability of small accommodation providers to market, regulatory and platform-related risks (e.g. dependence on OTAs and P2P platforms), which may raise their awareness of risk even when other PM tools remain underdeveloped. Thus, apartments may compensate for limited formal structures through a stronger perceived focus on risk identification and mitigation, an aspect that has been underexplored in prior hospitality PM literature.

Regarding the key performance indicators, hotels monitor time, cost, quality and ROI significantly more frequently, with medium to large effect sizes, which is in line with Kerzner's and PMI's view of these KPIs as the central pillars of professional project management and with the empirical work that stresses their universality across industries. The lower KPI usage in apartments suggests a reduced capacity to systematically evaluate project outcomes, reinforcing the maturity gap and supporting calls in the literature for targeted capacity-building and training in small tourism businesses.

By empirically comparing hotels and apartments within the same regional and institutional context, this study directly addresses the gap identified by Chalupa and Petriček (2020) and others concerning the lack of segment-specific, comparative analyses of project management practices in hospitality. The results demonstrate that hospitality cannot be treated as a homogeneous field: hotels and apartments differ not only in structural characteristics but also in their adoption of tools, software and KPIs, which has implications for both theory and practice.

In terms of theory, the findings suggest that existing PM maturity and toolset models developed for manufacturing or ICT sectors need to be adapted to capture the dual reality of highly formalized hotel projects and more flexible, risk-conscious but tool-poor apartment operations. In relation to practice, the study indicates two complementary directions: hotels should further integrate advanced planning structures (e.g. broader use of WBS/OBS and formal charters), while apartments would benefit most from basic formalization, simple software support, routine progress reporting, and systematic KPI tracking by building on their existing sensitivity to risk.

This research makes several original contributions that emerge from the empirical findings. First, it demonstrates that project management in Croatian hospitality is generally at a low level of maturity, and shows that hotels and apartments differ systematically in the degree of formalization and in the use of specific tools and indicators, and not just in overall intensity of PM adoption.

Second, by applying a detailed list of project management practices to two structurally different accommodation segments, the study reveals that even when apartments recognize the usefulness of certain tools, they use them significantly less frequently than hotels, highlighting a concrete "implementation gap" that the previous literature had not quantified. Third, the results nuance existing claims about digital and agile transformation in hospitality by showing that traditional tools (e.g. progress meetings, Gantt charts, formal reporting) are still not consistently embedded even in hotel practice, suggesting that the main challenge in this regional context is basic PM formalization rather than the adoption of advanced or AI-driven solutions.

5 Conclusions

The analysis compared project management practices between hotels and apartments in the Republic of Croatia, with the aim of identifying possible differences in the application of project management tools and indicators. The results indicate that there are no significant differences between hotels and apartments in the project selection phase; both groups use project selection methods to an equal extent, which suggests a uniformity of approach in the initial phase of the project cycle. However, significant differences were observed in the later phases of project management. Hotels organize kick-off meetings statistically significantly more often, which indicates a higher degree of formalization of the project initiation process. Furthermore, hotels use formal tools for project monitoring and evaluation to a greater extent, including programmatic performance monitoring, customer satisfaction surveys, and quality inspections. These practices contribute to a more systematic approach to project management and enable continuous monitoring of key performance indicators. Hotels also systematically monitor and manage fundamental aspects of projects, such as time, cost, quality and financial return, while apartments score lower on these parameters, which may indicate a less formalized process or limited resources. In the planning and organization segment, hotels more often apply structured methods such as WBS and OBS, as well as Gantt charts, which provide greater visibility and control over project activities.

Interestingly, apartments were the only ones to score higher in the area of risk identification, which may indicate greater awareness or specific challenges they face in their operations. On the other hand, hotels prepare budgets, define project scope statements, create lists of activities and conduct CBA analysis in more detail, which further confirms their more structured approach. Project documentation and records management (e.g. change requests, progress reports, meeting minutes, cost databases) is significantly more developed in hotels, which indicates a higher degree of formalization and systematicity in project management.

In the final stages, such as the database of contracts data and project takeover documentation, hotels also show a higher level of formalization, although the differences compared to apartments are less pronounced. The results of this analysis indicate that hotels apply a significantly more structured, formal and comprehensive approach to project management than apartments, which tend to use less formal and simpler project management methods. These differences can be attributed to the greater complexity of hotel projects, market demands and the need for standardization and quality control in the hotel industry.

The cluster analysis of business practices in hotels and apartments shows that there are four main groups of practices according to the frequency and importance of their application. The first group (green cluster) includes core business practices, such as cost database, budgeting and quality inspection, which are highly rated in both hotels and apartments, indicating their universal importance for accommodation management. The second group (orange cluster) includes formal project management practices, such as WBS, OBS and project charter, which are low rated in both sectors, probably due to the lower need for formalized processes in everyday work. The third group (blue cluster) contains practices with intermediate scores, which are used as needed, depending on the specifics of the project. The fourth group (purple cluster) includes practices that are highly rated in hotels but rarely applied in apartments, reflecting the higher degree of formalization and complexity in the hotel sector. In conclusion, the analysis indicates that core business practices are universally important, while formal tools and documentation are more characteristic of hotels and their application in apartments is limited.

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Appendix

Table A1: The 70 most used project management tools in order of average use

From Limited to Extensive Use	From Very Limited to Limited Use	Less Than Very Limited Use
Progress report Kick-off meeting PM software for task scheduling Gantt chart Scope statement Milestone planning Change request Requirements analysis Work breakdown structure Statement of work Activity list PM software for monitoring of schedule Lesson learned/post-mortem	Contingency plans Re-baselining Cost/benefit analysis Critical path method and analysis Bottom-up estimating Team member performance appraisal Team-building event Work authorization Self-directed work teams Ranking of risks Financial measurement tools Quality plan Bid documents Feasibility study Configuration review Stakeholders analysis	Life cycle cost (LCC) Database of contractual commitment data Probabilistic duration estimate (PERT) Quality function deployment Value analysis Database of risks

Baseline plan Client acceptance form Quality inspection PM software for resources scheduling Project charter Responsibility assignment matrix Customer satisfaction surveys Communication plan Top-down estimating Risk management documents	PM software for resources leveling PM software for monitoring of cost Network diagram Project communication room (war room) Project Web site Bid/seller evaluation Database of historical data PM software multiproject scheduling/leveling Earned value PM software for cost estimating Database for cost estimating Database of lessons learned Product breakdown structure Bidders conferences Learning curve Parametric estimating Graphic presentation of risk information	Trend chart or S-curve Control charts Decision tree Cause and effect diagram Critical chain method and analysis Pareto diagram PM software for simulation Monte-Carlo analysis

Source: Besner & Hobbs, 2006.

Managerial Disparities as a Barrier to Digital Transformation: A Pre-Reform Efficiency Baseline for Croatian Hospitals

Original scientific paper

Nikolina Dukić Samaržija[1]

ABSTRACT

This study establishes a pre-reform performance baseline to enable the future evaluation of Croatia's 2024 hospital sector reform, which centralized general hospital management under state ownership and introduced a new Public Health Protection Network. The research objective is to conduct a longitudinal assessment of the technical efficiency of Croatian general hospitals in the period immediately preceding this major structural change (2018–2023). The methodology employs Window Data Envelopment Analysis (WDEA), applying an input-oriented model with two inputs (beds, physicians) and two outputs (inpatient discharges, hospital days) to capture efficiency dynamics and trends. The analysis, while acknowledging the disruptive impact of the COVID-19 pandemic on the 2018–2023 trend, uncovers extreme and persistent inequality, with a 48-percentage-point gap between the most and least efficient hospitals in 2023. Decomposing efficiency shows that inefficiency is primarily driven by managerial performance (pure technical efficiency), while scale efficiency remains high and stable. These managerial disparities may also have implications for digital transformation of hospital operations, as the successful adoption of digital tools, from electronic health records to AI-driven diagnostic tools, often depends on underlying managerial capacity. The study concludes that the hospital reform must prioritize targeted interventions: the new state management should focus on elevating managerial practices in underperforming hospitals. Finally, this efficiency decomposition does more than rank hospitals; it diagnoses the specific nature of their inefficiency. This provides the new state owner with a precise, evidence-based map for prioritization and action in the post-reform period.

***Keywords**: Hospital efficiency, Window Data Envelopment Analysis (WDEA), Health sector reform, Public hospitals, Croatia*

***JEL classification**: I11, I18, C14, H51*

1 *Associate Professor, University of Rijeka, Faculty of Economics and Business, I. Filipovića 4, 51000 Rijeka, Croatia. Phone: +385 51 355 141. E-mail: nikolina.dukic.samarzija@efri.uniri.hr*

1 Introduction

Research on hospital efficiency is central to health policy, focusing on how healthcare institutions optimize resources to deliver quality care. The key areas of inquiry include the influence of hospital size and economies of scale, the impact of reimbursement models on incentivizing performance, and the role of management and technology adoption. Within this field, technical efficiency—the ability to maximize outputs from a given set of inputs—serves as a critical metric for assessing operational performance. Achieving gains in this area, however, must be carefully balanced with the imperative of maintaining equitable access to care, ensuring that efforts to improve efficiency do not inadvertently compromise service availability or quality.

The Croatian healthcare system provides a pertinent case for studying this balance, having undergone significant financial and structural pressures. Persistent systemic debt, exceeding half a billion euros in 2022 and largely attributable to hospitals, underscores chronic sustainability challenges. The sector's evolution through various reimbursement models—from fee-for-service to diagnosis-related groups (DRGs)—reflects ongoing attempts to enhance efficiency. While evidence suggests DRGs helped reduce the average length of stay (Bogut et al., 2012) and cost equalization (Dukić Samaržija et al., 2018), studies indicate that broader gains in cost efficiency have remained elusive over the past decade, with expenditures continuing to outpace activity (Kalanj, 2021). This context of financial strain and mixed reform outcomes sets the stage for a more profound structural change.

A defining feature of the Croatian hospital sector has been its fragmented governance. Clinical and specialized hospitals fall under state authority, while general hospitals—key providers of secondary care and significant contributors to system debt—have historically been managed by county and city governments. This decentralized model has complicated unified planning and accountability. In direct response, the Croatian government initiated a major organizational reform in 2024. This reform has two core pillars: (1) the transfer of general hospital management from local to state ownership, centralizing oversight and accountability, and (2) the establishment of a new Public Health Protection Network, designed to rationalize resource allocation by centralizing planning based on regional (county-level) needs (Ministry of Health, 2024).

This ambitious reform marks a pivotal transition. However, its long-term success and equitable implementation depend on rigorous, evidence-based monitoring and evaluation. A fundamental prerequisite for such an assessment is a clear, empirical understanding of the system's performance immediately before the reform's implementation. Without a robust pre-reform baseline, quantifying the true impact of centralization and the new Network becomes speculative.

Therefore, the purpose of this study is to provide an empirical, longitudinal assessment of the technical efficiency of Croatian general hospitals in the years immediately preceding this major structural reform. By quantifying and comparing efficiency levels and trends from 2018 to 2023, this research seeks to establish a crucial performance benchmark. This baseline will

enable future researchers and policymakers to conduct a valid counterfactual analysis, determining whether the 2024 reform—particularly the centralization of management and the operationalization of the Public Health Protection Network—has succeeded in enhancing the efficiency and equity of the hospital sector. In doing so, the study aims to shift the discussion from theoretical reform objectives to measurable outcomes grounded in pre-reform data.

2 Literature review

The efficiency of hospitals in Croatia is crucial because of the significant financial burden on the healthcare system. It serves as a key indicator of the system's overall quality and underscores the need for effective management strategies (Vašiček et al., 2018). Research shows that strong and adaptive management can significantly improve hospital efficiency, resulting in better outcomes and optimized resource utilization (Yousri et al., 2011; Collar et al., 2012; Waring & Bishop, 2010).

In health economics research, Data Envelopment Analysis (DEA) has become a fundamental tool for evaluating efficiency. The methodology's ability to compare the relative performance of healthcare systems, as well as the efficiency of the entire healthcare sector (Vajjhala & Eappen, 2024) based on their resource utilization and service output (Hollingsworth, 2008) has been instrumental in pinpointing inefficiencies, benchmarking performance across diverse settings, and informing policies for optimal resource use (Ozcan, 2014). The selection of appropriate inputs and outputs is a foundational step in DEA modelling. The established literature in health economics identifies a common set of variables: inputs commonly encompass human resources (medical staff), capital (beds, equipment), and financial expenditures, while outputs capture service volume (e.g., patient discharges) and, ideally, dimensions of care quality and outcomes (Zubir et al., 2024). This variable structure enables the comparative assessment of how efficiently different hospitals convert their resource base into healthcare services.

Although there are relatively few empirical studies looking specifically at hospital efficiency in Croatia, there are several notable studies examining the efficiency of healthcare systems more broadly. Buljan and Šimović (2022), for example, analyzed the efficiency of the Croatian healthcare system compared to 21 other EU countries using dynamic DEA window analysis. Their results show that the efficiency of Croatian health spending is lower compared to life expectancy, indicating the potential for better resource allocation. They suggest that Croatia could reduce the capacity of acute inpatient care while expanding outpatient care, which would lead to more cost-effective healthcare without compromising patient outcomes. Existing research on hospital efficiency in Croatia also includes county-level analyses. Rabar (2013) identified significant variations for the 2007–2009 period, and a later study by Arbula Blecich et al. (2024) for 2019–2022, noted shifts in county rankings, indicating dynamic performance over time. Hodžić et al. (2019) examined the efficiency of healthcare spending in 20 Croatian counties between 2010 and 2017 using the DEA methodology. Their study found significant differences in efficiency between counties, with only six counties showing efficient healthcare

spending. This underlines the need for targeted interventions to improve efficiency, particularly in underperforming counties. Further applying Window DEA to the period 2016–2022, Dukić Samaržija et al. (2024) also confirmed these persistent regional disparities in technical efficiency at county level.

At hospital level, Dukić Samaržija et al. (2018) evaluated the relative efficiency of public hospitals in Croatia using the DRG procedure K60B – diabetes without very severe and severe comorbidity and complications – and concluded that the introduction of the DRG reimbursement system in Croatian hospitals achieved its goal of leveling hospital cost structures and promoting performance. Kalanj (2022) examined the efficiency of 33 hospitals between 2009 and 2018, focusing on how remuneration models influence hospital performance. A recent DEA assessment of Croatian general hospitals (Dukić Samaržija, 2025) confirmed significant performance disparities. While some hospitals have adapted well to efficiency-oriented reforms, others continue to face structural and administrative barriers. However, these findings were primarily based on traditional, static DEA models, which provide only a cross-sectional snapshot of efficiency for a single time period. To move beyond static rankings and capture the dynamics of performance in the years immediately preceding the 2024 reform, this study employs a longitudinal approach using Window Data Envelopment Analysis (WDEA). This methodology treats a hospital in different years as distinct observations within a moving time window, allowing for the analysis of efficiency trends, stability, and the identification of persistent inefficiencies versus temporary fluctuations over the 2018–2023 period.

3 Methodology

This study employs a longitudinal, retrospective panel design to establish a baseline of technical efficiency for Croatian general hospitals in the immediate pre-reform period (2018–2023). The two fundamental models for efficiency evaluation are the CCR model (Charnes, Cooper & Rhodes, 1978), which assumes constant returns to scale (CRS), and the BCC model (Banker, Charnes & Cooper, 1984), which assumes variable returns to scale (VRS). These traditional DEA models provide a static, cross-sectional snapshot. In contrast, Window Data Envelopment Analysis (WDEA) introduces a dynamic perspective by treating DMUs in different years as distinct observations within a moving time window, allowing for the tracking of performance trends and stability (Asmild et al., 2004).

Given that hospitals typically do not operate at an optimal scale, an input-oriented model was selected. This orientation is appropriate for healthcare, where management has more direct short-term control over resource use (inputs) than over patient volume (outputs). The model identifies the potential proportional reduction in beds and physicians a hospital could achieve while maintaining its observed levels of discharges and hospital days.

Window DEA is an extension of the traditional DEA that introduces a dynamic element that allows for the measurement of DMU performance over time. In basic DEA models, DMUs are compared at a single point in time and treated as static units. In the real world, however, performance changes over time

due to technological advances, environmental conditions and other factors. Window DEA captures these changes by examining the efficiency of DMUs over multiple time periods. The observation period is divided into multiple time windows. Window DEA uses the moving average technique, which means that when observing changes over time, the earliest period in each shift window is replaced by the following period. In each window, a separate DEA analysis is performed, treating the observations within each window as different DMUs, allowing for a comparison of performance across different time periods. One of the main advantages of WDEA is that the performance of DMUs can be monitored over time, which is essential for understanding long-term efficiency trends. Managers can use the results of WDEA to optimize resource allocation, operations or strategy adjustments.

An efficiency score of 1 indicates that the Decision-Making Unit (DMU) is efficient. DMUs with a score below 1 are classified as inefficient. To properly interpret these results, it is essential to distinguish between the concepts of Technical Efficiency (TE), Pure Technical Efficiency (PTE), and Scale Efficiency (SE). In this study, overall technical efficiency (TE) was calculated using an input-oriented CCR model under the assumption of constant returns to scale (CRS). Pure technical efficiency (PTE) was calculated using an input-oriented BCC model under the assumption of variable returns to scale (VRS). This measure isolates managerial performance by eliminating the influence of scale. Finally, scale efficiency (SE) was derived as the ratio of TE to PTE (SE = TE/PTE).

4 Empirical data and analysis

The unit of analysis is an individual general hospital, which constitutes a decision-making unit (DMU). The study encompasses 22 general hospitals across Croatia. Data for the selected input and output variables were extracted from the official annual publications of the Croatian Institute of Public Health (Croatian Health Statistics Yearbook), ensuring reliability and consistency.

A fundamental challenge in DEA is variable selection, which must balance comprehensiveness with parsimony to avoid diluting the discriminatory power of the model. For this baseline study, the focus was narrowed to capture the core inpatient production function of general hospitals, a primary source of resource consumption and systemic debt. The following table lists selected inputs and outputs.

Table 1: DEA Model Variables: Inputs and Outputs

Variable	Description	Rationale
INPUTS		
1. Number of Beds	Total available inpatient beds.	Represents the primary capital investment and physical capacity of the hospital.

2. Number of Physicians	Full-time equivalent (FTE) practicing physicians.	Represents the core human capital and medical expertise for service delivery.
OUTPUTS		
1. Inpatient Discharges	Total count of completed inpatient stays.	Measures the volume of inpatient treatment episodes provided.
2. Hospital Days	Total inpatient bed days utilized.	Captures the intensity and duration of care, reflecting resource use over time.

Source: Author

This 2-input, 2-output configuration is deliberately parsimonious. To further justify the parsimony of the chosen model, several factors were considered. First, it focuses on the fundamental resources (bed capacity and medical staff) deployed to produce the key inpatient care outputs (treatment episodes and care days). While additional inputs (e.g., nurses, non-physician staff, capital equipment) and outputs (e.g., outpatient visits, quality indicators) are undeniably important, their inclusion would risk over-specifying the model given the sample size. Over-specification can lead to a loss of discrimination, where too many variables make most DMUs appear efficient. By focusing strictly on the fundamental resources (beds and physicians) and the primary volume-based outputs (discharges and hospital days), the most direct measure of technical efficiency in inpatient care is isolated. The choice of hospital days over simple patient counts is medically and economically significant, as it accounts for the resource intensity of longer stays, providing a more accurate gauge of the workload and efficiency in managing inpatient throughput (Wang et al., 2017). Second, this model structure is well-established in hospital efficiency literature (Fazria & Dhamanti, 2021) and satisfies the isotonicity assumption (positive correlation between inputs and outputs), a prerequisite for valid DEA application, as confirmed in our data.

For the six-year panel (T=6), a window length (*w*) of three years was chosen. This follows the rule of thumb to limit temporal heterogeneity while ensuring sufficient observations within each window for discriminative power (Asmild et al., 2004). This creates the following sequence of four overlapping windows: Window 1: years 2018, 2019, 2020; Window 2: years 2019, 2020, 2021; Window 3: years 2020, 2021, 2022; Window 4: years 2021, 2022, 2023. To assess the stability of these findings, a sensitivity analysis was conducted by re-running the Window DEA model with alternative window lengths (e.g., windows of 2 and 4 years). The relative rankings of hospitals and the aggregate trends in TE, PTE, and SE remained broadly consistent, suggesting that the identified patterns are not an artifact of the chosen 3-year window specification.

Within each window, the 22 hospitals across 3 years are treated as 66 distinct DMU-period observations. Over the four windows, a total of 264 DMU-period observations form the basis of the analysis. This window structure effectively enlarges the sample, significantly enhancing the model's ability to discriminate

between hospitals and identify robust trends. The analysis was conducted using DEA Solver Pro software.

The combination of a focused 2x2 variable set and WDEA is strategically chosen to fulfil the specific purpose of this study: parsimonious and interpretable baseline, dynamic trend analysis and robustness with limited DMUs. The simplified model strips away complexity to highlight fundamental efficiency in core inpatient care. This creates a clear, unambiguous benchmark centered on bed and physician productivity, which are direct levers for the new state management and Public Health Protection Network. WDEA transforms six annual data points into a moving efficiency profile for each hospital. This is critical for distinguishing between one-year anomalies and persistent inefficiency trends in the pre-reform era. Finally, with 22 DMUs, a traditional DEA model using 4 variables is at the lower bound of acceptability. WDEA mitigates this by expanding the effective sample to 264 observations, ensuring stable and reliable frontier estimation and efficiency scores suitable for a national baseline study.

Table 2: Descriptive Statistics of Input and Output Variables (2018-2023)

Variable	Mean	SD	Minimum	Maximum
Beds	288.38	177.76	76.00	934.00
Physicians	113.31	63.35	19.67	250.33
Inpatient Discharges	10,453.14	5,602.61	3,064.33	24,907.00
Hospital Days	64,575.47	40,708.04	17,135.33	208,516.33

Source: Author

Descriptive statistics for the period 2018-2023 (Table 2) reveal substantial variation across hospitals, confirming the heterogeneity in scale and activity that the efficiency analysis will assess.

5 Results and discussion

Efficiency is assessed by decomposing overall performance into three distinct components, as established in the DEA literature (Al-Refaie et al., 2016; Kumar and Gulati, 2008): technical efficiency (TE), pure technical efficiency (PTE), and scale efficiency (SE). TE, often referred to as overall efficiency, is based on CRS. It evaluates how well resources are utilized and distributed between DMUs and shows the ability to efficiently convert inputs into outputs. The TE can be broken down into its main components PTE and SE. PTE, which functions according to the VRS, measures management's performance in organizing inputs and the influence of external factors and excludes scale

efficiency. SE provides information on optimal production size and resource utilization and indicates how well DMUs optimize the use of their inputs. It can be calculated by dividing TE and PTE.

To derive a stable, summary measure of each hospital's performance over the entire observed period, the cross-period average efficiency score (C-average) was calculated. This score represents the mean efficiency of a hospital across all windows in which it appears, smoothing out annual fluctuations and providing a robust indicator of its persistent performance level during the pre-reform era. Table 3 shows the C-averages for each hospital, which represent the average across all three efficiency components - TE, PTE and SE. A score of 1 means that a DMU is fully efficient compared to other hospitals in the sample, while a score below 1 indicates relative inefficiency.

Table 3: Results of TE, PTE and SE – C – Average

	C-Average-TE	C-Average-PTE	C-Average-SE
Zabok	0.848208613	0.892732434	0.950126354
Sisak	0.672215199	0.681386036	0.986540908
Karlovac	0.758520238	0.763324752	0.993705807
Ogulin	0.725789574	0.813421117	0.892267927
Varaždin	0.840428662	0.941374936	0.892767197
Koprivnica	0.764662735	0.845235108	0.904674602
Bjelovar	0.630033003	0.708223284	0.889596568
Gospić	0.954660647	0.999999573	0.954661054
Virovitica	0.88116277	0.921155609	0.956584057
Požega	0.775685073	0.784687213	0.988527735
Pakrac	0.866422912	0.894213481	0.968921774
Slavonski Brod	0.728073485	0.756918454	0.961891576
Nova Gradiška	0.702134209	0.76964444	0.912283871
Zadar	0.824645188	0.9127538	0.903469466
Našice	0.809518471	0.853048702	0.94897099
Šibenik	0.762765176	0.78274413	0.974475754
Knin	0.888495776	0.911496195	0.974766303
Vinkovci	0.847291172	0.857379541	0.988233486
Vukovar	0.487212341	0.534680003	0.911222299
Pula	0.759111674	0.80245883	0.945982082
Dubrovnik	0.696908353	0.703709974	0.990334625

Čakovec	0.981297754	0.982026425	0.999257993
Average	0.782056501	0.823300638	0.949511929

Source: Author

As shown in Table 3, the average scores establish the national pre-reform benchmark: TE - 0.782, PTE - 0.823, SE - 0.950.

This indicates that, on average, Croatian general hospitals could produce the same level of outputs using 21.8% fewer resources if they were fully technically efficient (1 - 0.782 = 0.218). The primary driver of this overall inefficiency are managerial and operational practices (PTE), not scale. The high average SE score (0.950) suggests that, in aggregate, hospitals are operating close to their optimal size. The critical inefficiency lies in how they utilize their given scale.

The decomposition allows us to categorize hospitals into distinct profiles, which is essential for the new state management and Public Health Protection Network to design targeted interventions.

Table 4. Hospital efficiency profiles: Diagnosis and reform priorities

Profile	Defining Characteristic	Primary Cause of Inefficiency	Key Reform Lever & Priority
Benchmarks	High TE, High PTE, High SE	None (efficient)	Lever: Peer learning Priority: Model and replicate best practices
Managerial Challenge	Low TE, Low PTE, High SE	Managerial and operational processes	Lever: State ownership and oversight Priority: High. Direct intervention and support
Scaling Challenge	Low TE, Moderate PTE, Low SE	Suboptimal Size/Scale	Lever: Public health protection network Priority: High. Regional restructuring
General Improvement	Moderate TE, PTE, and SE	Mixed managerial and scale factors	Lever: Systematic monitoring Priority: Medium. Gradual enhancement

Source: Author

Gospić (TE: 0.955, PTE: ~1.000, SE: 0.955) and Čakovec (TE: 0.981, PTE: 0.982, SE: 0.999) are the system's benchmark hospitals. They demonstrate

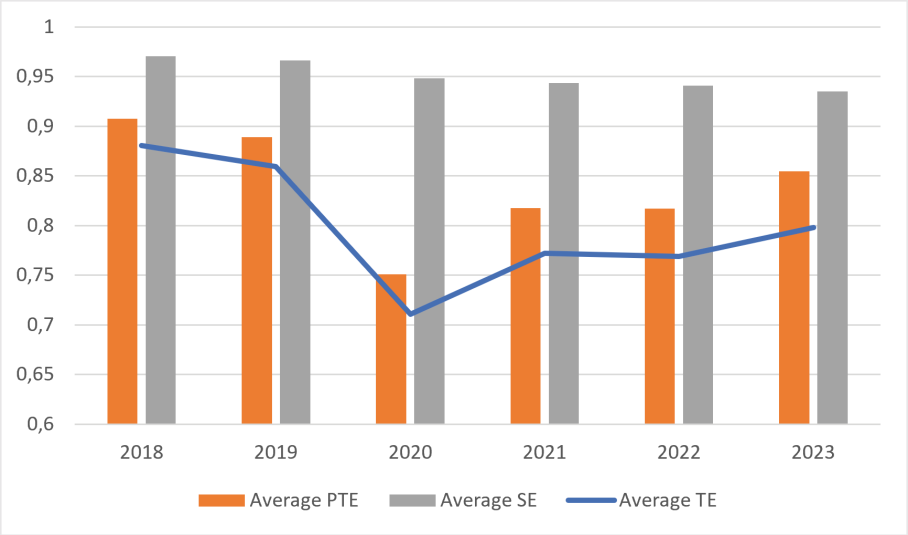
excellent management (near-maximum PTE) and operate at an optimal scale (near-maximum SE). Their practices should be studied and potentially replicated. Čakovec's status as an efficiency benchmark is consistent with its high performance in external clinical quality assessments, such as the DLI5 audit of 28 hospitals (Agencija za kvalitetu i akreditaciju, 2017), where it excelled across indicators for acute myocardial infarction, stroke, and antimicrobial prophylaxis.

Hospitals that exhibit managerial challenges are Vukovar (TE: 0.487, PTE: 0.535, SE: 0.911) and Bjelovar (TE: 0.630, PTE: 0.708, SE: 0.890). Vukovar was ranked among the top 40% in the DLI5 audit for all three clinical categories (Agencija za kvalitetu i akreditaciju, 2017), yet it is the least technically efficient hospital in our study. This shows that a hospital can deliver care that adheres to clinical guidelines (quality) but at an excessively high resource cost (inefficiency). They do not convert inputs into outputs effectively due to processes, organization, or external constraints. Consequently, these institutions emerge as priority targets for direct managerial support and process re-engineering under the new centralized authority.

Their inefficiency stems from operational deficiencies rather than issues of scale. Ogulin (TE: 0.726, PTE: 0.813, SE: 0.892) and Varaždin (TE: 0.840, PTE: 0.941, SE: 0.893) have relatively good managerial efficiency (decent PTE) but operate at a suboptimal scale. Their SE score indicates they are either too small to benefit from economies of scale or too large facing diseconomies. These hospitals require strategic, regional-scale planning - potential consolidation, redefinition of service scope, or resource reallocation - to align their operational scale with regional need. Most other hospitals (e.g., Sisak, Karlovac, Požega) exhibit moderate inefficiency from a combination of both managerial and scale factors. They require systematic monitoring and incremental improvements under the new framework.

The Window DEA results reveal the technical efficiency landscape of Croatian general hospitals in the immediate pre-reform period, as shown in Figure 1.

Figure 1: Trends in PTE, SE, and TE for Croatian General Hospitals, 2018-2023



Source: Author

Average technical efficiency (TE) followed a pronounced 'shock and partial recovery' trend, declining sharply in 2020 and remaining approximately 8 percentage points below pre-pandemic levels by 2023. This aggregate trend was driven almost entirely by changes in pure technical efficiency (PTE), while scale efficiency (SE) remained consistently high.

However, the interpretation of this trend requires a critical acknowledgment of the exogenous shock caused by the COVID-19 pandemic. The sharp decline in 2020 is almost certainly a reflection of the pandemic's disruption to normal hospital operations, such as the postponement of elective procedures, redeployment of staff, and increased infection control measures, rather than a sudden deterioration of underlying managerial capability. Consequently, the "baseline" established for 2023 is, in part, a "post-shock" baseline that captures a system still recovering from these temporary disruptions. This has two important implications for the study's findings. First, the persistent gap between 2023 efficiency and pre-pandemic levels suggests that either the structural inefficiencies were exacerbated by the crisis or that the system had yet to fully return to its operational equilibrium. Second, and more importantly for the reform, the classification of hospitals into efficiency profiles (e.g., Managerial Challenge) should be viewed with caution. A hospital like Vukovar, identified as highly inefficient, may have experienced a slower or more difficult recovery from the pandemic compared to its peers. Therefore, while the Window DEA methodology smooths out some yearly volatility, the 2023 snapshot inevitably carries the legacy of the pandemic.

The low PTE, indicating managerial shortcomings, finds a compelling

explanation in the independent Study of Croatian Physicians reflecting the perceptions of 29% of the nation's practicing doctors (Hrvatska liječnička komora [HLK], 2025). The study reveals a system where physicians rate the quality of management at just 4.7 out of 10 and report critical deficits in working conditions. More than half state they lack sufficient time for patients and must cover multiple worksites, while only a third are satisfied with medical equipment. These factors directly degrade the quality of the inputs (physician labor and capital) modeled in this efficiency analysis. Hospitals with low PTE scores are likely those where these negative workplace conditions, as reported by the HLK, are most acute, leading to suboptimal resource utilization. Beneath this average, however, lay extreme and persistent disparities. In 2023, TE scores ranged from a maximum of 1.00 (Čakovec, Knin) to a minimum of 0.52 (Vukovar) - a gap indicative of a deeply unequal system.

This analysis offers a clear strategic imperative for the reform. The role of the Public Health Protection Network is to safeguard the sector's existing high scale efficiency, while the central mandate for the new state management is to drive improvements in PTE. Consequently, the key metric for evaluating the reform's success will be its capacity to increase and maintain PTE, which will directly determine the recovery and enhancement of overall technical performance.

This study has several limitations that also define the agenda for future inquiry. First, the DEA model focuses on technical efficiency using readily available volume metrics (discharges, bed days) and does not account for differences in care quality or case-mix complexity. Second, the pre-reform period includes the anomalous shock of the COVID-19 pandemic, which may affect trend interpretation. Finally, as a non-parametric method, WDEA identifies but does not statistically explain the root causes of inefficiency. While the findings are contextualized using external sources (e.g., HLK, 2025), a formal second-stage regression analysis of the efficiency determinants remains a necessary step for future research to move from diagnosis to prescribed solutions.

These limitations direct future work. Subsequent research should incorporate quality-adjusted outputs and a broader set of inputs to measure value-based efficiency. Employing second-stage regression analysis on the efficiency scores generated here would help identify the specific managerial, technological, and environmental determinants of performance. Most importantly, the definitive baseline established in this paper enables a rigorous ex-post impact evaluation. Future studies could replicate this analysis with post-2024 data to quantify the reform's effect. Complementary qualitative case studies of hospitals from different efficiency profiles would provide the contextual understanding needed to translate diagnostic maps into effective managerial action.

6 Conclusions

This study has established a critical empirical benchmark by conducting a longitudinal assessment of the technical efficiency of Croatian general hospitals in the immediate pre-reform period (2018–2023). Applying Window Data Envelopment Analysis (WDEA) to a parsimonious model of core inputs

and outputs, the research quantified the sector's performance on the eve of a major structural transformation.

The analysis yields three pivotal findings. First, it reveals a system characterized by extreme and persistent inequality, with a performance gap of over 48 percentage points between the most and least efficient hospitals in 2023. Second, decomposing efficiency demonstrates that this inefficiency is primarily managerial in nature, driven by deficits in pure technical efficiency (PTE), while scale efficiency (SE) remains consistently high and stable. Third, this decomposition enables the creation of a diagnostic efficiency map, categorizing hospitals into distinct profiles, such as those requiring urgent managerial intervention versus those needing strategic resizing. These managerial disparities may also have implications for digital transformation of hospital operations, as the successful adoption of digital tools, from electronic health records to AI-driven diagnostic tools, often depends on underlying managerial capacity.

Consequently, the study's primary contribution is to move beyond a simple performance ranking. It provides the reform authorities with an evidence-based action framework. The new state management must prioritize elevating managerial practices in hospitals with low PTE, such as Vukovar and Bjelovar. Simultaneously, the Public Health Protection Network has a clear mandate to address specific scale inefficiencies in hospitals like Ogulin and Varaždin through regional planning.

By shifting the focus from theoretical reform goals to measurable outcomes, this study establishes a critical pre-reform benchmark. It suggests that the success of Croatia's hospital centralization should be evaluated against a dual metric: the reduction of the profound efficiency disparities identified here and the sustainable elevation of managerial performance. Addressing these managerial gaps is not only essential for operational efficiency but also lays the groundwork for successful digital advancement in the post-reform period. This task now falls on the Public Health Protection Network, which must integrate clinical quality and technical efficiency data to tailor interventions (supporting inefficient but high-quality hospitals like Vukovar, while replicating the model of efficient performers like Čakovec). Future assessments must remain mindful that this baseline captures a system still recovering from the pandemic's operational shock.

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Education-R&D-Digitalization as a Recipe for Achieving Sustainable Development in European Countries

Original scientific paper

Snežana Radukić[1], Vesna Buterin[2], Vesna Janković-Milić[3]

ABSTRACT

Investments in education, research and development, and digital infrastructures, influence the level of digitalization and serve as a lever for achieving sustainable development in countries. The aim of the paper is first to examine the impact of these factors on a country's digitalization level, and then to assess whether the degree of digitalization has an impact on the environmental dimension of sustainable development in European countries. It is assumed that the level of education, amount of investment in research and development and the quality of the digital infrastructure can enhance the level of digitalization and sustainable development in a country through innovation, application of new production technologies, extension of product life cycles, recycling etc. This paper examines the impact of investments in higher education and research and development (R&D), and the development of digital infrastructure on the ecological footprint in European countries over the past five years. Investment in higher education and R&D is expressed as a percentage of GDP, whereas the development of digital infrastructure is measured by indicators such as the number of internet users and mobile telephony penetration. The methodological framework is based on a panel data analysis of selected European countries. The data originate from relevant international statistical sources, including Eurostat and the Global Footprint Network. The results indicate a complex and multidimensional relationship between investments in knowledge, technological development, digitalization and a country's environmental performance. The paper contributes to the existing literature by highlighting the importance of integrated education,

1 *Full professor, University of Niš, Faculty of Economics, Trg kralja Aleksandra Ujedinitelja 11, 18000 Niš, Serbia. Scientific affiliation: microeconomics, sustainable development. Phone: +381641494800. E-mail: snezana.radukic@eknfak.ni.ac.rs.*

2 *Associate professor, University of Rijeka, Faculty of Economics and Business, Ivana Filipovića 4, 51000 Rijeka, Hrvatska. Scientific affiliation: macroeconomics, economic theory, institutional development. Phone: +38551355122. E-mail: vesna.buterin@efri.uniri.hr.*

3 *Full professor, University of Niš, Faculty of Economics, Trg kralja Aleksandra Ujedinitelja 11, 18000 Niš, Serbia. Scientific affiliation: statistics, sustainable development. Phone: +381641965262. E-mail: vesna.jankovic@eknfak.ni.ac.rs.*

innovation, and digital development policies aimed at achieving environmentally sustainable development.

***Keywords**: Investment in higher education, Investment in research and development (R&D), Digital infrastructure, Ecological footprint*

***JEL classification**: H52, O38, Q55, Q56, C33*

1 Introduction

Digital transformation has become one of the central features of socio-economic development in the last decade, especially in European countries, which increasingly see digitalization as a key instrument in strengthening competitiveness, fostering innovation and achieving sustainable development goals. At the same time, growing environmental pressures, including climate change, ecosystem degradation and increasing ecological footprint, impose the need for development models that integrate technological progress with efficient management of natural resources. In this context, digitalization is increasingly recognized not only as an economically, but also as a potentially ecologically relevant phenomenon.

Investments in higher education, research and development (R&D) and digital infrastructure are fundamental determinants of the level of a country's digitalization. Advanced human capital and a strong research and innovation base enable the creation and application of new technologies, while an accessible and high-quality digital infrastructure provides the prerequisites for their widespread application in the economy and society. Numerous studies indicate that such investments stimulate technological progress, increase productivity and accelerate structural changes, but their effects on the environmental dimension of sustainable development have not yet been clearly established.

On the one hand, digitalization can lead to increased energy and resource consumption, especially through the growth of data centres, electronic waste and the more intensive use of digital devices. On the other hand, digital technologies enable the optimization of production processes, and allow for a more efficient energy management, reduction of material consumption and the development of circular business models. Innovations driven by investments in knowledge and technology can result in the extension of product life cycles, achievement of more advanced recycling systems and reduced negative environmental impacts. Therefore, the relationship between digitalization and environmental sustainability can be characterized as complex, multidimensional and strongly conditioned by the institutional and developmental context.

Despite the growing interest in this topic, the empirical literature that simultaneously analyses the impact of investments in education, research and development and digital infrastructure on the level of digitalization, as well as the indirect or direct impact of digitalization on environmental sustainability,

remains relatively limited, especially in the European context. Most existing studies focus on individual aspects of digital transformation or on the economic effects of investments in knowledge, while the environmental dimension is often marginalized or analysed in isolation.

The aim of this paper is therefore twofold. First, it examines the impact of investments in higher education and research and development, and the development of digital infrastructure on the level of digitalization in European countries. Second, it analyses the impact of the level of digitalization on the environmental dimension of sustainable development, as measured by the ecological footprint. The empirical analysis is based on panel data from selected European countries for the last five years, using data from relevant international statistical sources. The contribution of the paper is to provide empirical evidence on the interrelationships between investment in knowledge, digitalization and environmental sustainability, and to highlight the importance of integrated policies in the areas of education, innovation and digital development in achieving long-term sustainable development.

2 Literature review

Across Europe, education systems and R&D capacity are increasingly positioned as catalytic levers through which digitalization accelerates sustainable development, yet the literature consistently shows that this “recipe” works only when digital transformation is treated as a socio-technical change rather than a narrow technology upgrade. In higher education, often framed as a core institutional actor for advancing the Sustainable Development Goals, recent reviews converge on the view that digital transformation can contribute to sustainability by (i) building sustainability competencies, (ii) enabling smart and sustainable campus operations, and by (iii) strengthening the conceptual and theoretical integration between digitalization and sustainability agendas (Trevisan et al., 2024).

Complementing this, a research focusing on the Fourth Industrial Revolution argues that digital transformation in higher education can support sustainable curricula, improve student performance, and enhance innovation capacity, while anticipating near-term trajectories such as Education 4.0, gamification, datafication in decision-making, and wider integration of artificial/augmented intelligence (Shenkoya & Kim, 2023). Importantly, multivocal evidence suggests that many universities remain at early stages of digital maturity: initiatives are frequently launched as isolated projects rather than embedded in an integrated strategy, with advanced analytics, cloud solutions, and AI being prominent technology choices but often deployed without the governance coherence needed for high institutional return (Fernández et al., 2023). This strategic gap is echoed in broader discussions of digital transformation challenges in higher education institutions, where barriers around policy design, institutional readiness, and organizational change complicate the translation of digital investments into sustained educational and environmental gains (Rodrigues, 2017). Strategy-oriented perspectives further underline that digital transformation can be leveraged to build universities’ competitive advantage, but only when embedded into decision support and evolutionary

learning mechanisms that continuously align institutional vision, student experience, and changing external demands (Mohamed Hashim et al., 2022). Within this strategic framing, the intersection of sustainability and educational transformation is increasingly described as a “dual challenge”. Namely, institutions must expand their digital capability whilst also protecting inclusivity and ensuring that sustainability goals are not subordinated to market or efficiency logics (Kotula & Malagocka, 2025).

Empirical and policy-oriented analyses within Europe reinforce that these institutional dynamics are inseparable from national and regional digital ecosystems. For example, an analysis of EU member states indicates that technological infrastructure and IT use are consistently strong determinants of digital economy development, while human capital, especially education and digital skills, becomes more influential over time; intellectual assets (e.g., patents and research outputs) also emerge as increasingly important, particularly in later years, signalling the growing relevance of R&D outputs for digital performance as measured through DESI and related innovation indicators (Roszko-Wójtowicz et al., 2024). Jovanović et al. (2018) use DESI to measure the digital competitiveness of EU member states and analyse how digital performance is related to the main components of sustainable development: economic, social and environmental dimensions. Based on the correlation between DESI and other composite indices that measure the components of sustainable development, they proved that digitalization has a positive effect on economic growth and the social dimension, whereas the environmental component tends to be neglected, with digitalization exerting a moderately negative impact. A parallel study on digital competitiveness across thirty European countries, using multi-criteria composite methods with Eurostat indicators, similarly highlights that digital readiness, technological capability, and learning/application capacity differentiate leaders from laggards; Nordic countries tend to cluster at the top of digital competitiveness, whereas many Eastern European countries remain behind, with measurable links between digital competitiveness and macroeconomic performance (Stankovic et al., 2021). Accordingly, a comparative analysis of European countries based on the available data from the DESI 2022 index, revealed that the Western Balkan countries lag behind the EU member states, and that in order to accelerate the narrowing of the digital gap between these two groups of countries, it is recommended to intensify investments aimed at developing digital skills, modernizing infrastructure, strengthening the digitization of small and medium-sized enterprises, as well as improving the quality and availability of public digital services (Stevanović & Petrović-Ranđelović, 2025).

Country and subregional studies provide additional nuance about how R&D and skills link to digitalization pathways: in the Baltic States, correlations using Eurostat data suggest that the number of R&D specialists and patterns of internet use in banking, both associated with broader economic development, align with faster digitalization, implying that workforce composition and digitally mediated economic behaviour can act as practical conduits for digital transition (Stecenko & Stukalina, 2022). In Central Europe’s Visegrad Group, indicator-based examination connecting DESI dimensions with SDG target indicators underscores that digital performance varies substantially across countries and relates to sustainability outcomes in ways that can be benchmarked and

ranked, revealing both strengths and shortcomings within the group's digital–sustainability linkage (Esses et al., 2021).

A consistent theme across these comparative and econometric approaches is that digitalization is uneven, and that disparities in infrastructure, skills, and innovation systems shape whether digital transformation reinforces or undermines sustainable development trajectories. This point is also reflected in studies of regional heterogeneity outside the EU core, where digital transformation can correlate with sustainable development indicators while simultaneously producing trade-offs: in Russian regions, multi-level regression and panel models suggest that "digital labour" and "digital capital" are important drivers of socio-economic outcomes and correlate with regional digital transformation. At the same time, structural economic composition (e.g., manufacturing share) shows more complex associations, with evidence that increases in manufacturing share may coincide with decreased regional sustainable development, highlighting that digitalization interacts with sectoral structure rather than uniformly enhancing sustainability (Mirolubova and Radionova, 2023). Earlier work on "digital readiness" monitoring in Russia similarly stresses that transition readiness depends on identifiable factors and can be summarized through aggregated indices, while also linking digital transformation to sustainable development through innovative and intellectual effects, indicating the role of measurement systems in guiding policy and investment priorities (Kozhevina et al., 2019).

The acceleration of economic growth in the future can be stimulated by increased government investments in public infrastructure and fundamental scientific research, tax incentives and subsidies linked to private sector innovations, as well as by promoting entrepreneurship and reforming the education system (Arsić, 2020). The higher education–R&D nexus is explicitly articulated in research that treats universities not only as training systems but also as research and innovation engines for the digital economy: analyses of higher education adaptability argue that educational, research, and innovation components are structurally connected to digital economy development, and propose a digital adaptability strategy grounded in systemic and synergetic approaches and in deepened stakeholder partnerships aligned with a Quadruple Helix logic (Kholiavko et al., 2020). At the institutional "micro" level, research on regional universities emphasizes that digitizing research management, through conceptual apparatuses, priority setting, and digital modules based on business analytics, can strengthen universities' innovation contributions to regional development, thereby linking R&D governance to digital transition capacity (Petruk & Shashlo, 2020).

Alongside these academic proposals, evidence-based assessments in specific European-adjacent contexts (notably Ukraine) underscore that digitalization strategies must integrate infrastructure expansion, e-governance, regulatory alignment, cybersecurity, and inclusivity if they are to translate ICT adoption into EU-aligned sustainable development values. ICT-driven analyses in Ukraine frame IoT, AI, blockchain, and cloud computing as cross-sector enablers for economic, social, and environmental sustainability, but emphasize that barriers such as insufficient infrastructure, economic disparity, and digital divides must be addressed through coordinated policy measures and digital

literacy initiatives (Lysenko and Makovoz, 2025). Related strategy-focused assessments of Ukraine's economy similarly argue that digital transformation can enhance efficiency and competitiveness and should prioritize innovative sectors, digital services in public administration and business, the strengthening of data protection and cybersecurity, positioning these as prerequisites for sustained modernization rather than optional add-ons (Shcherban et al., 2025). A factor-identification analysis in Ukraine proposes integrated indices and component-based evaluation approaches that highlight the relative strengths (e.g., self-sufficiency, efficiency, readiness) as well as weaknesses (e.g., low involvement), suggesting that the sustainability payoff of digitalization depends on a policy's ability to broaden participation and cooperation, not merely raise technical capacity (Vasyltsiv et al., 2022).

Finally, country-specific EU-facing analyses, such as the review of Romania's higher education indicators and EU-level readiness initiatives, reinforce that the green and digital transitions are intertwined at the performance-indicator level, with digital skills development and systemic monitoring presented as central to progress (Fleaca et al., 2022). Taken together, this body of work indicates that Education–R&D–digitalization can function as a coherent pathway toward sustainable development in European countries when (a) higher education digital transformation is strategically integrated rather than fragmented, (b) human capital and research outputs are treated as drivers of digital economy performance alongside infrastructure, and when (c) policies actively manage unevenness by addressing inclusion, cybersecurity, and governance capacity. However, a persistent research gap remains in demonstrating causally robust, longitudinal linkages between specific university digital transformation initiatives, measurable R&D outputs, and downstream SDG progress across diverse European regions, particularly where digital maturity is low and socio-economic constraints are high (Fernández et al., 2023; Trevisan et al., 2024).

3 Data and methodology

The sample consists of 36 European countries for which data were available for the entire observed 2020-2024 period. Relevant international statistical databases, including Eurostat and the Global Footprint Network, were used as sources for the analysis within this research. Table 1 shows the average values of the variables by year, as well as the standard deviation.

Table 1: The mean and the standard deviation of selected variables

Year		Internet users	Mobile telephony penetration	Investment in higher education	Investment in R&D	EF_ production
2020	Mean	121.1359	1.068	87.0292	1.6214	4.2486
	Std. Deviation	16.52254	0.431	8.46516	.96386	2.30232

2021	Mean	120.6370	1.096	89.1343	1.6097	4.4472
	Std. Deviation	15.35651	0.421	7.13912	.96402	2.33002
2022	Mean	123.1716	1.692	90.0792	1.5927	4.3686
	Std. Deviation	16.10238	0.451	5.91819	.95014	2.36567
2023	Mean	125.8503	1.468	91.3619	1.6300	4.1942
	Std. Deviation	18.62208	0.415	5.54537	.97657	2.32371
2024	Mean	125.7559	1.080	92.7059	1.7705	4.1378
	Std. Deviation	18.86469	0.374	4.92209	.96989	2.27413

Notes: Internet users (% in total population); Mobile telephony penetration - Mobile cellular subscriptions (per 100 people); Investment in higher education (% of GDP); Investment in R&D (% of GDP); EF_production - Ecological Footprint of production (in global hectares) divided by the population of the respective country.
Source: Authors

Table 1 presents the descriptive statistical indicators for key variables over the period 2020–2024. The results reveal pronounced time trends as well as changes in the degree of variability among the observed units.

The average number of internet users shows a steady increase throughout the observed period, rising from 121.14 in 2020 to 125.76 in 2024. This trend indicates continuous improvement in digital connectivity. At the same time, the increase in the standard deviation suggests growing dispersion among the observed units, which may point to the widening differences in the level of digital inclusion.

Mobile telephony penetration exhibits certain fluctuations. After relatively stable values in 2020 and 2021, a significant increase is recorded in 2022, followed by a decline in 2023 and 2024. The decrease in the standard deviation over time indicates a gradual reduction in cross-country differences, which may reflect market saturation and convergence in mobile telephony infrastructures.

Investment in higher education demonstrates a clear upward trend. The average value of this variable increased from 87.03 in 2020 to 92.71 in 2024, indicating the growing importance of education in development strategies. At the same time, the continuous decline in the standard deviation suggests a reduction in inequalities in investment levels among the observed countries and a convergence of education policies.

Investment in research and development remains relatively stable over the observed period, with a slight increase in 2024. The largely unchanged standard deviation points to the persistence of structural differences among countries, suggesting that the innovation gap remains a challenge despite the general recognition of the importance of R&D activities.

The ecological footprint of production shows a slight increase up to 2021,

followed by a gradual decline toward the end of the observed period. This trend may be interpreted as an indication of improved environmental efficiency in production processes or a shift toward more sustainable production patterns. The slight decrease in the standard deviation further indicates a gradual convergence in environmental performance across countries.

Overall, the descriptive analysis points to positive developments in digitalization, education, and environmental sustainability, while investment in research and development remains relatively stable, which may represent a limiting factor for long-term innovative and sustainable growth.

4 Results and discussion

The sample included 36 European countries for which complete data were available. The empirical analysis employs a regression analysis of panel data based on balanced panel dataset that covers the period from 2020 to 2024. As shown in Table 2, the dependent variable in the model is Ecological footprint of production, while regressors include Investment in higher education (expressed as percentage of GDP), Investment in R&D (expressed as a percentage of GDP), Internet users (share in total population) and Mobile telephony penetration measured by Mobile cellular subscriptions (per 100 people). Total number of observations equals 180. In order to control unobserved heterogeneity across countries and over time, the model incorporates both cross-section and time fixed effects.

Table 2: Research variables

Variable	Indicator	Measure	Source	Label
Dependent variable	Ecological footprint of production	in global hectares divided by the population of the country	Global Footprint Network	EF_ production
Independent variable	Investment in higher education	% of GDP	Eurostat	HE
	Investment in R&D	% of GDP	Eurostat	R&D
	Internet users	% of total population	Eurostat	IU
	Mobile telephony penetration	Mobile cellular subscriptions per 100 people	Eurostat	MTP

Source: Authors

Since the data include multiple variables observed over time, a panel regression analysis based on the panel least squares method was employed,

allowing for the simultaneous consideration of temporal and cross-sectional structural variations. This approach is particularly suitable for the analysis of environmental and development indicators, as it increases the number of observations, reduces the problem of multicollinearity, and allows for more efficient estimates compared to traditional cross-sectional or time-series models.

The t-test was used to assess the statistical significance of individual regression coefficients, testing the null hypothesis that a given coefficient is equal to zero. In this way, the test determines whether individual explanatory variables have a statistically significant effect on the ecological footprint of production at conventional significance levels. The overall statistical significance of the model was evaluated using the F-test, which examines the joint explanatory power of all independent variables included in the model. A high F-statistic accompanied by a probability close to zero indicates that the model is statistically significant as a whole and that the explanatory variables jointly account for variations in the dependent variable.

The R-squared and adjusted R-squared coefficients were employed to assess the proportion of variance in the ecological footprint of production explained by the model. Their high values indicate a good fit of the model to the data, while the adjusted R-squared additionally accounts for the number of regressors and sample size.

To examine the potential presence of autocorrelation in the residuals, the Durbin–Watson test was applied as a standard diagnostic tool in panel and time-series analyses. This test is essential for evaluating the independence of the error terms and for ensuring the reliability of standard errors and the validity of statistical inference.

Table 3: Results of regression analysis

Dependent variable: Ecological footprint of production Method: Panel least squares Periods included: 5 Cross-sections included: 36 Total panel (balanced) observation: 180				
Variable	Coefficient	Standard error	t-statistic	Probability
Constant	2.406	0.991	2.426	0.016
Investment in higher education	-0.358	0.214	-1.673	0.096
Investment in R&D	0.020	0.009	2.160	0.032
Internet users	-0,004	0,002	-2,237	0,028

Mobile telephony penetration	0.003	0.004	0.829	0.408
R-squared: 0.993				
Adjusted R-squared: 0.991				
S.E. of regression: 0,208				
F-statistic (probability): 49.622 (0.000)				
Durbin-Watson statistic: 1.467				

Source: Authors

According to the results presented in Table 3, the estimated model demonstrates a very strong explanatory power, because, based on the coefficient of determination, it explains 99 percent of the total variability of the dependent variable. Regarding the regression coefficients, the Number of internet users exhibits a positive and statistically significant effect on Ecological footprint of production, at the 5% significance level. In addition, Investment in higher education shows a negative coefficient, that is statistically significant at the 10% level.

In contrast, Investment in research and development does not display a statistically significant relationship with Ecological footprint of production. This outcome may indicate that R&D expenditures require a longer time horizon to translate into measurable productivity gains, or that their effects are already captured by the fixed effects included in the model. Similarly, the variable Mobile telephony penetration exhibits a positive but statistically insignificant coefficient.

5 Conclusions

Education systems and R&D capacity in Europe are increasingly recognized as key drivers through which digitalization can promote sustainable development. However, the literature consistently emphasizes that this approach is effective only when digital transformation is framed as a socio-technical process, involving institutional change, human capital development, and organizational adaptation, rather than merely as a technological upgrade or the adoption of new tools. In other words, the full potential of digitalization for sustainability is realized when it is embedded within broader educational, research, and governance strategies that align technological adoption with economic, social and environmental objectives.

This study examined the relationship between higher education, R&D and digitalization, and the ecological footprint of production across European countries using a balanced panel dataset over five years. The estimated panel regression model demonstrates a very high explanatory power, explaining approximately 99% of the total variability in the ecological footprint of production. The results indicate that the number of internet users has a positive and statistically significant effect on the ecological footprint at the 5% level, suggesting that increased digital connectivity is associated with higher

production-related environmental pressure. In contrast, investment in higher education exhibits a negative coefficient, significant at the 10% level, implying that greater educational investment may contribute to the reduction in the ecological footprint, potentially through the development of sustainability competencies and more efficient production practices. However, investment in research and development does not exhibit a statistically significant effect, which may be due to the longer time required for R&D to influence measurable productivity or because its impact is already absorbed by the fixed-effects model. Similarly, mobile telephony penetration has a positive but insignificant coefficient, indicating that basic connectivity alone is not sufficient to impact production-related environmental outcomes.

Consistent with the recent literature, higher education is increasingly recognized as a central institutional actor in advancing sustainability, contributing through the development of sustainability competencies, promotion of sustainable campus operations, and integration of digitalization with sustainability agendas (Trevisan et al., 2024; Shenkoya and Kim, 2023). Digital transformation in universities is seen as a socio-technical process that requires alignment of human capital, governance, and technological capabilities to effectively support the Sustainable Development Goals (Fernández et al., 2023; Mohamed Hashim et al., 2022). Empirical evidence also emphasizes that the broader digital ecosystem, including internet penetration, R&D outputs, and technological infrastructure, is essential for translating digitalization into measurable sustainability impacts, though outcomes are uneven across countries and regions depending on policy coherence, institutional readiness, and socio-economic conditions (Roszko-Wójtowicz et al., 2024; Jovanović et al., 2018; Stanković et al., 2021). Internet usage is negatively related to the ecological footprint, supporting evidence that broader digital inclusion can promote more efficient and sustainable production practices (Stecenko and Stukalina, 2022). These findings support the broader argument that digitalization and innovation contribute to sustainability only when embedded within coherent socio-technical strategies, where higher education, R&D, and digital infrastructure are aligned with environmental objectives, rather than pursued as isolated technological upgrades (Fernández et al., 2023; Mohamed Hashim et al., 2022).

Overall, these findings highlight the differentiated roles of digitalization, education, and innovation in shaping environmental sustainability, suggesting that human capital development may have a more immediate mitigating effect on production-related environmental impacts than technology investments alone. The results emphasize the importance of conducting additional long-term studies that connect particular digital, educational and R&D initiatives to quantifiable progress on the Sustainable Development Goals. The analysis suggests that while increased internet use is associated with a higher ecological footprint, strategic investment in higher education can mitigate environmental impacts, highlighting that the Education–R&D–Digitalization nexus serves as a critical pathway for advancing sustainable development in European countries.

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Appendix

Table A1. The list of 36 European countries used as a sample in the research

Number	Country
1.	Austria
2.	Belgium
3.	Bosnia and Herzegovina
4.	Bulgaria
5.	Croatia
6.	Cyprus
7.	Czechia
8.	Denmark
9.	Estonia
10.	Finland
11.	France
12.	Germany
13.	Greece
14.	Hungary
15.	Iceland
16.	Ireland
17.	Italy
18.	Latvia
19.	Lithuania
20.	Luxembourg
21.	Malta
22.	Montenegro
23.	Netherlands
24.	North Macedonia

25.	Norway
26.	Poland
27.	Portugal
28.	Romania
29.	Serbia
30.	Slovakia
31.	Slovenia
32.	Spain
33.	Sweden
34.	Switzerland
35.	Turkey
36.	United Kingdom

Source: Authors according to available data from Eurostat and the Global Footprint Network

Organizational Culture and Job Satisfaction in Crisis Conditions: Evidence from a Pandemic Context

Original scientific paper

Mirjana Grčić Fabić[1], Irena Turčić[2], Boštjan Antončič,[3] Jasna Auer Antončič[4]

ABSTRACT

This paper examines the relationship between organizational culture and employee job satisfaction in crisis conditions, using a large-scale crisis as the empirical setting. The research aims to assess whether specific dimensions of organizational culture explain variations in overall job satisfaction and its key facets. In addition, the study investigates whether differences in job satisfaction emerge across dominant organizational culture types. Particular attention is also given to employees' perceptions of potential shifts in organizational culture during a period of disruption. The study was conducted among employees from micro to large organizations in both the public and private sectors in Croatia. Data were collected through an online survey. The analysis relied on correlation and regression analysis. Open-ended responses were examined to gain further insight into perceived cultural changes. The findings indicate that flexibility represents a significant predictor of overall job satisfaction as well as its individual dimensions. Differences in job satisfaction were identified across organizational culture types, with clan culture exhibiting the strongest positive association with overall job satisfaction. Respondents also reported noticeable shifts in cultural characteristics, particularly toward greater flexibility, digitalization of work processes, and changes in communication patterns.

1 *Associate Professor, University of Rijeka, Faculty of Economics and Business, Ivana Filipovića 4, 51000 Rijeka, Croatia. Phone: +38551355103. E-mail: mirjana.grcic.fabic@efri.uniri.hr.*

2 *M.Econ, MIDIA Ltd., Veslarska 3, 51000 Rijeka, Croatia. Phone: +38551321458. E-mail: irena.midia@gmail.com.*

3 *Full Professor, University of Ljubljana, School of Economics and Business, Kardeljeva ploščad 17, 1000 Ljubljana, Slovenia. Phone: +386 1 589 25 25. E-mail: bostjan.antoncic@ef.uni-lj.si.*

4 *Full Professor, University of Primorska, Faculty of Management, Izolska vrata 2, 6000 Koper, Slovenia. Phone: +386 5 610 20 00. E-mail: jasna.auer@fm.upr.si.*

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***JEL classification**: M12, M14, D23*

1 Introduction

Given the increasing awareness of its impact on employee attitudes and organizational outcomes, organizational culture has emerged as a key concept in management and organizational behaviour research since the 1980s (Lund, 2003). Later studies relied more on quantitative models that made it easier to compare different types of cultures and how they relate to organizational variables. Early studies, on the other hand, mostly used qualitative methods (Gregory, 1983). The conceptualization of organizational culture as an organizational-level variable (Smircich, 1983) made it possible to examine how organizational culture can be influenced and controlled as a strategic asset. Recent meta-analytic evidence (Hartnell et al., 2011) shows that some cultural orientations are always connected to how employees feel and how well they do their jobs. The Competing Values Framework (Cameron & Quinn, 1999) is one of the most widely used frameworks. It divides cultures into four types: clan, adhocracy, market, and hierarchy. It also points out the tension between flexibility and stability as a key cultural dimension.

Job satisfaction is another concept that has been extensively studied in the field of organizational behaviour (Locke, 1976). Still, it is gaining increasing attention in theory and in practice, especially when studied in complex and uncertain context (Spector, 2022). Previous studies consistently demonstrate that organizational context and leadership practices influence employee satisfaction levels. However, the mechanisms by which cultural characteristics function during crisis situations remain inadequately investigated. Empirical studies in Croatia have investigated organizational culture and job satisfaction independently (Bahtijarević-Šiber, 1992; Barać et al., 2015; Mečev & Grubišić, 2020). Yet their interrelationship has not been systematically analysed, particularly during periods of significant disruption.

Crisis settings are a very important test of how well an organization is set up and how well its managers do their jobs. Amid large-scale crises, work organization, processes of communication, decision-making and employee expectations must all change quickly (Kim et al., 2023; Kim, 2020). Recent research conducted during global disruptions indicate that adaptive, internally focused, and flexible cultures may mitigate adverse employee reactions and enhance well-being. In contrary, rigid and control-oriented cultures may exacerbate dissatisfaction and stress. Nonetheless, empirical evidence is fragmented, particularly in smaller economies and transitional settings. Consequently, this paper investigates the correlation between organizational culture and employee job satisfaction within Croatian organizations functioning under crisis conditions. Special attention is given to the role of flexibility, different types of organizational culture and employees' perceptions of potential cultural shifts during disruption.

Based on the defined research problem and empirical evidence, the subsequent hypotheses are put forth:

H1: It is expected that hierarchical culture will be the most prevalent type of organizational culture, with employees reporting moderate overall job satisfaction and varying levels of satisfaction across its specific dimensions.

H2: Different types of organizational culture are positively related to overall job satisfaction and its dimensions, with clan and adhocracy cultures showing the strongest positive relationships.

H3: Flexibility, as an important part of organizational culture, is strongly linked to overall job satisfaction and its various dimensions.

H4: There are strong differences in job satisfaction levels between different types of dominant organizational cultures, with employees in clan and adhocracy cultures showing more beneficial levels of satisfaction in relation to market and hierarchical cultures.

H5: Crisis conditions are linked with perceived shifts in organizational culture.

The rest of the paper is structured as follows. The next section presents the literature review and theoretical underpinnings. The third section outlines the research methodology and data analysis. The following section presents the empirical results, followed by discussion and the paper ends with conclusions, which include practical implications and guidelines for future research.

2 Literature review

2.1 Organizational culture

In the 1980s, interest in researching the concept of organizational culture expanded as managers became aware of the effect of organizational culture on employees and the organization (Lund, 2003). Organizational culture is a powerful tool for achieving desired outcomes (Hogan & Coote, 2014) because it directs the implementation of decisions in the organization and enables strategy setting (Martins & Terblanche, 2003). It refers to the assumptions, beliefs, and values that employees share with each other and transfer to new members about the organization and procedures for solving and dealing with problems (Schein, 1990; Schneider et al. 2012). In order for a culture to be effective, it must also be efficient and in accordance with the needs of the organization, employees and the activities that the organization performs (Wallach, 1983). Therefore, managers (leadership) play a major role in organizational culture, as they must recognize the fundamental dimensions of their organization's culture and the impact that these dimensions have on variables related to employees, such as satisfaction, commitment, cohesion, strategy implementation, performance, etc. (Lund, 2003). In the beginning, research on organizational culture was mainly qualitative (Gregory, 1983), whereas later research opted for a quantitative approach (Cameron & Freeman, 1991) in order to compare different types of cultures more easily, along with their characteristics as well as the connection of organizational

culture with other concepts.

The complexity of the concept of organizational culture is reflected in different definitions, theoretical models, and approaches to measuring organizational culture. These approaches differ in the determinants that organizational culture encompasses (Ostroff et al., 2003). According to Wallach (1983), there are three types of organizational culture: bureaucratic, innovative and supportive. Handy (1986) proposed four types of organizational cultures; power culture, role culture, task-oriented culture and people-oriented culture. The Competing Values Framework (CVF) is a theoretical model developed by Quinn and Rohrbaugh (1981). This composite model highlights the values found within the four models; model of human relations, model of open system, model of rational goals and model of internal processes. By summarizing previous research (Quinn and Rohrbaugh, 1981, 1983; Quinn and McGrath, 1982; Smircich, 1983), Cameron and Freeman (1991) developed a typology of organizational cultures according to CVF and labelled them clan, adhocracy, market and hierarchical cultures, adding attributes that represent or correspond to each type. Clan culture emphasizes the long-term welfare of employees through human resource development, cohesion and morale. Success is reflected in the care for their employees and in paying special attention to their customers. Adhocracy is a type of culture that makes an organization a dynamic and creative place to work. The success of an organization is measured through uniqueness and the new products or services it can offer and it encourages employees to take initiative and freedom. Market culture is an organizational culture that is exclusively result-oriented, therefore, in such organizations, the competitive spirit is extremely emphasized. Hierarchical organizational culture is extremely formalized and structured. Success in such organizations is defined through reliable delivery, low costs, and good organization. The Competitive Values Model and the Organizational Culture Model of Cameron and Quinn (1999) represent the theoretical framework for assessing organizational culture in this research.

2.2 Employee job satisfaction

Job satisfaction is a concept that has been used in organizational research for many years. Locke (1969) states that the growth of interest and research into the concept of job satisfaction began in the 1930s after Hoppock (1935) published his book entitled Job Satisfaction. In his book, Spector (2022) argues that the interest in researching this concept has grown over the years and that it is still at the centre of researchers' interest. There are many definitions that have attempted to operationalize job satisfaction. Szromek and Wolniak (2020) list 11 definitions that are most commonly used in job satisfaction research, although there are many more. Locke (1969) defines job satisfaction as a pleasant emotional state that results from an individual's personal assessment of their job, i.e. job satisfaction (dissatisfaction) results from the difference that an individual perceives between what they want from their job and what they get for it, or what they believe they deserve for it. Job satisfaction consists of three components: the owner's perception of the aspects of their job, personal implicit and explicit value standards, and conscious or unconscious judgments of the overlap between the perceived and personal value standards. Spector

(2022) defines job satisfaction as the feeling that people have towards their job and the different aspects of their work, and when assessed generally, it represents an individual's attitude towards the work they do. Aziri (2011) believes that job satisfaction is a feeling that arises from the perception that the job satisfies the material and psychological needs of the individual.

Spector (2022) summarized the most common facets (dimensions) of job satisfaction that can be found in research, specifically in instruments for assessing job satisfaction: communication, coworkers (colleagues), material and non-material benefits, working conditions, nature of work, organization, organizational rules, salary, personal growth, opportunity for advancement, gratitude, recognition, job security, and superiors. Locke (1976) had previously grouped satisfaction facets into four areas: nature of work (job tasks), organizational context (rules and practices), reward (salary and benefits), and social environment (colleagues and superiors). Auer Antončič and Antončič (2011) analysed employee satisfaction dimensions in the context of intrapreneurship. According to their research, overall job satisfaction, workplace relationships, pay, benefits, organizational culture, and employee loyalty represent key antecedents of intrapreneurship. They developed and tested a model in which employee satisfaction fosters intrapreneurship and, in turn, contributes to firm growth. On that way, they demonstrated that both employee satisfaction and intrapreneurship are associated with higher company growth. Recent empirical studies indicate that job satisfaction is influenced by contextual factors. According to Jo and Shin (2025) and Nemteanu et al. (2021) some of these factors are leadership style, organizational support, perceived fairness, and job security. In unstable settings, levels of satisfaction may vary based on how organizations handle change, convey uncertainty, and safeguard employee welfare.

2.3 Organizational culture and job satisfaction in crisis contexts

There are many studies in the literature that use the Competing Values Framework and four types of culture: clan, adhocracy, market, and hierarchical culture when examining the relationship between culture and job satisfaction. One of them was conducted by Lund (2003). The results showed that job satisfaction is highest in clan and adhocracy cultures, followed by market, and lowest in hierarchical cultures across the four culture types. He also examined the relationship between organizational cultures and job satisfaction and found that clan and adhocracy are positively related to job satisfaction, while market and hierarchical are negatively related. Later studies did not find such relationships. In the study by El Badawy et al. (2016), all four culture types are positively related to job satisfaction, with the highest correlation between clan culture and job satisfaction. Sow et al. (2017) found that in the American healthcare industry, adhocracy and market culture are significant predictors of job satisfaction. Taskiran et al. (2017) also examined job satisfaction in the healthcare industry, specifically among hospital employees, but they obtained slightly different results. Clan and adhocracy cultures are significant predictors of job satisfaction and increase job satisfaction. Whereas the presented studies

examined overall job satisfaction, there is less research focusing on individual dimensions of job satisfaction and organizational culture. One such study was conducted by Belias et al. (2015). They examined the relationship between organizational culture and job satisfaction in the banking sector in Greece. Significant relationship was found between salary and job satisfaction, while other dimensions of job satisfaction (working conditions, promotion, job and superiors) were not significantly associated with culture types. Adhocracy and market culture were negatively associated with salary, while hierarchical culture showed a positive relationship. Zavyalova and Kucherov (2010) examined organizational culture and job satisfaction across 12 different aspects (salary, bonuses, and benefits, managers' attitudes toward employee needs, work organization, career opportunities, managers' objectivity in evaluating employees, managerial style and methods, awareness of the organization's operations, employee morale, etc.) in Russian companies from various industries. The results showed that overall job satisfaction is highest in clan cultures and adhocracy, followed by hierarchical and market cultures. By comparing different cultures and aspects of job satisfaction, they found that employees in hierarchical cultures are most satisfied with salaries, managers' attitudes toward employee needs, and the awareness of the organization's operations; in market cultures, the employees are most satisfied with the influence that employees have on decisions related to personal issues; in clan cultures, they are most satisfied with work organization, employee morale, and the possibility of professional growth; while in adhocracy, the employees are most satisfied with managers' objectivity in evaluating performance, the opportunity to demonstrate skills and creativity, and the possibility of professional growth.

Some studies have used the typology of organizational cultures from Wallach (1983), specifically bureaucratic, innovative and supportive cultures, when examining the relationship with job satisfaction. For example, Silverthorne (2004) found a statistically significant difference in job satisfaction with respect to the organizational cultures of companies in Taiwan. Organizations with innovative and supportive cultures had higher job satisfaction compared to bureaucratic ones, while organizations with innovative and supportive cultures did not differ. Huey Yiing and Zaman Bin Ahmad (2009) found that all three culture types are significantly related to each other and also to job satisfaction. The strongest correlation with job satisfaction was found for supportive culture.

Other studies have also examined the relationship between organizational culture and job satisfaction. Azanza et al. (2013) conducted a study of 571 employees from 114 Spanish private companies from various industries and found that a flexible organizational culture significantly explains the variance in job satisfaction. Tsai (2011) examined organizational culture (dimensions - employee orientation, customer focus, emphasis on responsibility, emphasis on cooperation) and job satisfaction (dimensions - satisfaction with colleagues, rewards and benefits, superiors, recognition) and reported that all dimensions are significantly correlated. The results of the presented studies show that regardless of the complexity of the constructs of organizational culture and job satisfaction and the different methods of measurement, some common links can be found. It can be concluded that in flexible organizational cultures such as clan and adhocracy, job satisfaction is higher compared to market and

hierarchical ones.

Crises that come from outside can represent a threat by having an effect on the functioning, success and survival of organizations (Wenzel et al., 2020; Puthusserry et al., 2022; Frutos-Bencze et al., 2022; Mockaitis et al. 2022). The COVID-19 pandemic represents a form of crisis that can be characterized as a "black swan" event (Winston, 2020). These events have a low probability of occurrence, but have a large negative impact on the economy and society. In their literature review, Puthusserry et al. (2022) reported that those organizations that had more flexible organizational structures were more resilient and innovative in responding to external crises, but also that the size of the organization was an important factor. Large organizations with highly formalized structures may find it more difficult to adapt to crises by introducing changes. Flexibility is a big challenge for companies that are based on control, rigid structure and hierarchy (Azanza et al., 2013). In the field of risk management, research indicates that organizations whose cultures have traits such as flexibility and adaptability adapt best to crises (Deverell & Olsson Gardell, 2010).

Considering the above, organizations whose cultures have a pronounced dimension of flexibility are more resistant to crises and adapt more easily to changes in the environment. Since a pandemic represents a form of crisis that affects all organizations, it can be expected that organizations with a flexible structure (clan and adhocracy) implement changes more quickly and effectively and thus may cope with the crisis more easily. In a clan culture, mutual support among members and a sense of family could play an important role in the organization's adaptation during the pandemic, since this crisis is not only financial but also health-related, while in an adhocracy, innovation and adaptability could play a key role. Therefore, it is to be expected that employees in these types of cultures are more satisfied with their jobs during the pandemic than those in organizations whose structures are not as flexible and thus find it harder to adapt to changes.

Since there is much less research examining individual dimensions of job satisfaction and organizational culture, additional research is needed to examine these relationships. It should also be noted that, to the author's knowledge, no research has been conducted in Croatia that has put organizational culture and job satisfaction into perspective. This research will attempt to contribute to clarifying these relationships and provide additional insight given the specific context (time of crisis/pandemic) in which the research was conducted.

3 Methodology

3.1 Sample

A non-probability sampling method was used to collect the data, and convenience sampling method was employed. An online survey was conducted to collect data from March to May 2022. Before answering the questions, participants were informed about the study and the issue of privacy and anonymity. Informed consent was obtained electronically. Tables 1 and 2 present the demographic characteristics of the survey participants and the profiles of their organizations.

Table 1: Frequencies, means, standard deviations, and ranges of respondents' demographic characteristics

		f	%	M	SD	Range
Gender	Female	121	62.4	1.38	0.49	1–2
	Male	73	37.6			
Age	21–30	49	25.3	38.44	10.59	21–64
	31–40	73	37.6			
	41–50	40	20.6			
	Above 50	32	16.5			
Education level	Primary school	1	0.5	3.57	0.89	1–5
	Secondary school	29	15.0			
	College degree / Bachelor's degree	44	22.7			
	University degree / Master's degree	98	50.5			
	Master of Science / PhD	22	11.3			
Organizational tenure	1–3 years	56	28.9	9.61	8.95	1–41
	4–6 years	48	24.7			
	7–14 years	41	21.1			
	15–41 years	49	25.3			

Source: Authors

Table 2: Frequencies and percentages of the organizations in which the respondents are employed

		f	%
Number of employees	2–9	28	14.4
	10–49	42	21.7
	50–249	45	23.2
	250 and more	79	40.7
Organizational sector	Public sector	100	51.5
	Private sector	94	48.5

Industry (NACE Classification)	A: Agriculture, Forestry and Fishing	1	0.5
	C: Manufacturing	8	4.1
	D: Electricity, Gas, Steam and Air Conditioning Supply	2	1.0
	E: Water Supply; Sewerage, Waste Management	2	1.0
	F: Construction	5	2.6
	G: Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles	14	7.2
	I: Accommodation and Food Service Activities	8	4.1
	J: Information and Communication	12	6.2
	K: Financial and Insurance Activities	30	15.5
	L: Real Estate Activities	1	0.5
	M: Professional, Scientific and Technical Activities	15	7.7
	N: Administrative and Support Service Activities	6	3.1
	O: Public Administration and Defence; Compulsory Social Security	21	10.9
	P: Education	32	16.5
	Q: Human Health and Social Work Activities	20	10.3
	R: Arts, Entertainment and Recreation	4	2.1
	S: Other Service Activities	11	5.7
	T: Activities of Households as Employers; Undifferentiated Goods and Services-Producing Activities of Households for Own Use	1	0.5
	U: Activities of Extraterritorial Organizations and Bodies	1	0.5

County of employment	Bjelovar-Bilogora	1	0.5
	Brod-Posavina	1	0.5
	City of Zagreb	87	44.9
	Istria	6	3.1
	Karlovac	1	0.5
	Koprivnica-Križevci	1	0.5
	Krapina-Zagorje	1	0.5
	Lika-Senj	4	2.1
	Osijek-Baranja	3	1.5
	Primorje-Gorski Kotar	60	30.9
	Sisak-Moslavina	4	2.1
	Varaždin	7	3.6
	Virovitica-Podravina	1	0.5
	Zadar	1	0.5
	Zagreb County	16	8.3

Source: Authors

The questionnaire was filled out by 208 people in total. Fourteen responses were omitted from subsequent analysis based on established criteria: self-employed individuals without employees, tenure under a year, and organizations in operation under two years. The final sample included 194 employees from micro, small, medium, and large organizations in both the public and private sectors. Most of the respondents were women, and the age distribution was fairly even, with the largest group being between 31 and 40. Most of the people who took part had at least a college degree. Most of the respondents worked for large companies (with 250 or more employees), and the number of participants from the public and private sectors was nearly the same. The sample was drawn primarily from the City of Zagreb and Primorje-Gorski Kotar County, and the most common industries included education, finance and insurance, and public administration. In general, the sample indicates a wide variety of workers across different sectors and industries, including many employees from large public institutions.

3.2 Variables and data analysis

To examine organizational culture and job satisfaction, the Croatian versions of the OCAI (Organizational Culture Assessment Instrument) and the Job Satisfaction Questionnaire were used. A five-point Likert scale for OCAI was employed. The metric characteristics and factor structure for the Croatian version were examined by Mečev and Grubišić (2020). The Croatian version of the Job Satisfaction Questionnaire has been translated and validated on a Croatian sample (Krapić, Ćoso & Sušanj, 2006). The scale examines overall job satisfaction on a five-point Likert scale and its five dimensions; satisfaction with salary, satisfaction with advancement opportunities, satisfaction with

the job itself, satisfaction with superiors, and satisfaction with coworkers. In addition, a categorical variable of changes in organizational culture was also used, which sought to examine whether participants perceived any changes in organizational culture compared to the period before the pandemic (When you compare organizational culture (values, attitudes, informal rules, communication, leadership style, organizational focus...) before the pandemic and today, have you noticed that any changes have occurred? - the possible answer was yes or no). Qualitative data on perceived changes in culture were also collected based on an open-ended question (If you answered yes to the previous question, please state what changes you have noticed?) in order to gain additional insight into possible changes in organizational culture.

IBM SPSS version 25 was used to process quantitative data. Exploratory factor analysis was conducted for OCAI (the factor extraction method was the principal component method with direct oblimin rotation). The factor analysis indicated four factors; however, all items did not load on the latent factors as theoretically assumed. In accordance with the survey, where respondents indicated whether they perceived changes in organizational culture before and during the pandemic, the factor structure was examined separately for those who perceived a change in organizational culture and those who did not. Factor analysis showed a cleaner structure in respondents who did not perceive a change. Measures of internal consistency, coefficient alpha (Cronbach alpha), were also checked. The obtained values are shown in Table 3.

Table 3: Internal consistency measures for organizational culture types

	Clan culture	**Adhocracy**	**Market culture**	**Hierarchy culture**	**Overall organizational culture**
All respondents	0.830	0.841	0.808	0.694	0.920
Respondents – perceived cultural change	0.777	0.798	0.808	0.625	
Respondents – did not perceive cultural change	0.858	0.867	0.809	0.741	

Source: Authors

Cronbach's alpha coefficients show that when all respondents are included, all measures for assessing culture types show good internal consistency, except for the hierarchical type, which is at the threshold of acceptability. It is also evident that, for respondents who reported no change in organizational culture, all types demonstrate good reliability, while for the hierarchical type, internal consistency is acceptable. Given the results obtained, the initial scale with all items was used. Composites were created for each culture type, as well as a composite for the flexibility dimension that was used in further analysis. Dummy variables were also created for organizational culture types.

In the next step, the factor structure for the Job Satisfaction Questionnaire was examined (principal axis factoring with direct oblimin rotation). Five factors were obtained, and Cronbach's alpha coefficients were calculated for each dimension and overall job satisfaction. Table 4 shows the results indicating good to excellent reliability.

Table 4: Cronbach's alpha coefficients for job satisfaction dimensions

Job Satisfaction Dimension	α
Work Itself	0.839
Promotion	0.874
Pay	0.911
Co-workers	0.828
Supervision	0.766
Overall Job Satisfaction	0.916

Source: Authors

4 Results and discussion

For the purpose of testing the first hypothesis, descriptive statistics were calculated and are presented in Table 5.

Table 5: Descriptive statistics for job satisfaction dimensions, overall job satisfaction, and organizational culture

	Job Satisfaction						Organizational Culture			
	Pay	Supervision	Coworkers	Promotion	Work Itself	Overall	Clan	Adhocracy	Market	Hierarchy
M	2.97	3.32	3.61	2.86	3.48	3.25	3.28	3.09	3.18	3.64
SD	1.05	0.81	0.77	0.99	0.88	0.64	0.82	0.83	0.81	0.65
Skewness	-0.06	-0.33	-0.44	-0.12	-0.60	-0.19	-0.18	-0.30	-0.40	-0.58
Kurtosis	-0.70	-0.35	-0.08	-0.74	0.11	-0.35	-0.51	-0.31	-0.35	0.71
Minimum	1.00	1.00	1.17	1.00	1.00	1.53	1.17	1.00	1.00	1.33

Maximum		5.00	5.00	5.00	5.00	5.00	4.70	5.00	5.00	5.00	5.00
Percentiles	25	2.17	2.83	3.17	2.17	3.00	2.80	2.67	2.50	2.67	3.17
	50	3.00	3.33	3.67	3.00	3.50	3.30	3.33	3.17	3.25	3.67
	75	3.71	3.83	4.17	3.50	4.17	3.73	4.00	3.67	3.83	4.00

Source: Authors

The results indicate that hierarchical culture is the most prevalent organizational culture type (42.2%), followed by clan (16.7%), market (14.6%), and adhocracy (6.3%). In 20.3% of organizations, no single dominant culture type was identified, suggesting the coexistence of multiple cultural elements. When only organizations with a clearly dominant culture were considered, hierarchical culture remained predominant. Regarding job satisfaction, employees reported moderate overall levels. They were most satisfied with their coworkers and least satisfied with promotion opportunities. The expectation that salary would be the lowest-rated dimension was not confirmed; therefore, the **H1** hypothesis was only partially supported.

Pearson correlation coefficients were subsequently calculated and are presented in Table 6.

Table 6: Correlation coefficients for organizational culture types and job satisfaction

	Clan Culture	**Adhoc-racy**	**Market Culture**	**Hierar-chical Culture**	**Job Satis-faction (Work Itself)**	**Salary Satis-faction**	**Super-visor Satis-faction**	**Co-worker Satis-faction**	**Pro-motion Satis-faction**	**Overall Job Satis-faction**
Clan Culture	-									
Adhocracy	0.77**	-								
Market Culture	0.40**	0.65**	-							
Hierarchical Culture	0.60**	0.48**	0.46**	-						
Job Satisfaction (Work Itself)	0.37**	0.33**	0.10	0.11	-					
Salary Satisfaction	0.29**	0.22**	0.24**	0.27**	0.33**	-				
Supervisor Satisfaction	0.52**	0.31**	0.02	0.36**	0.38**	0.22**	-			

Coworker Satisfaction	0.43**	0.28**	0.04	0.32**	0.20**	0.22**	0.54**	-		
Promotion Satisfaction	0.53**	0.49**	0.31**	0.39**	0.54**	0.45**	0.48**	0.42**	-	
Overall Job Satisfaction	0.60**	0.46**	0.22**	0.41**	0.70**	0.67**	0.71**	0.64**	0.83**	-

Note: **p < 0.001

Source: Authors

There were strong and positive correlations between all types of organizational culture. Overall job satisfaction exhibited a significant positive correlation with all culture types, with the most robust association identified for clan and the least for market culture. All aspects of job satisfaction were significantly correlated with overall satisfaction; however, not all cultural types exhibited significant associations with every dimension of satisfaction. For example, market culture did not have a big effect on how happy people are with their coworkers, superiors, or the work itself, and as for hierarchical culture, on how happy people were with the work itself. In general, clan culture had the strongest and most consistent links to satisfaction dimensions, while market culture had the weakest. These results partially validate the H2 hypothesis, indicating that flexibility and internally focused cultures are more significantly associated with employee satisfaction.

To test the third hypothesis, simple linear regressions were conducted. Simple regression analysis showed that flexibility is a significant predictor (β=0.57, p<0.001) of overall job satisfaction F (1,190)=89.14, p<0.001 and explains 31.9% of the variance with a high effect size (f2=0.47). The results show that flexibility is a significant predictor of all dimensions of job satisfaction. It explains the most variance in satisfaction with promotion (29.5%), followed by satisfaction with superiors (19.4%), and the least variance in satisfaction with salary (7.5%). It is evident that the effect of flexibility on satisfaction with promotion is large, on satisfaction with salary is small, and on the remaining dimensions of job satisfaction it is medium. This confirms hypothesis **H3**.

Table 7: Regression analysis results: flexibility as predictor of job satisfaction dimensions

Criterion	b	S.E. b	β	R^2	t	Model Summary
Job Satisfaction (Work Itself)	0.43	0.08	0.38	0.140	5.56**	F(1,190)=30.99, p<0.001, f^2=0.16
Promotion Satisfaction	0.70	0.07	0.54	0.295	8.93**	F(1,190)=79.67, p<0.001, f^2=0.42
Supervisor Satisfaction	0.46	0.07	0.44	0.194	6.77**	F(1,190)=45.84, p<0.001, f^2=0.24

Coworker Satisfaction	0.39	0.07	0.38	0.145	5.68**	F(1,190)=32.30, p<0.001, f²=0.17
Salary Satisfaction	0.38	0.10	0.27	0.075	3.92**	F(1,190)=15.36, p<0.001, f²=0.08

Note: p < 0.001
Source: Authors

To test the fourth hypothesis, which examined whether employees differ in job satisfaction depending on the dominant organizational culture type, multiple regression analyses were conducted. Dummy variables for organizational culture were included, and only respondents from organizations with a clearly dominant culture type were retained in the analysis (N = 153). Prior to conducting the regressions, statistical assumptions were verified. Levene's tests for homogeneity of variance were non-significant across variables, indicating equal variances between groups. Multicollinearity was not detected (VIF<3.5; Tolerance > 0.1), and normality of dependent variables had been previously confirmed. As all assumptions were satisfied, regression analyses were performed. Results for satisfaction with coworkers are presented in Table 8.

Table 8: Differences in coworker satisfaction by organizational culture

Criterion		Predictors	B	S.E.	t	Model Summary
Coworker satisfaction	Model 1	Constant	3.64	0.22	16.4**	R=0.263, R²=0.069, F(3,149)=3.68, p<0.05, f²=0.074
		Hierarchical	-0.11	0.24	-0.48	
		Clan	0.31	0.26	-1.34	
		Market	-0.31	0.27	-3.78	
	Model 1a	Constant	3.95	0.14	29.09**	
		Hierarchical	-0.43	0.16	-2.67**	
		Market	-0.63	0.19	-3.15**	
		Adhocracy	-0.31	0.26	-1.21	
	Model 1b	Constant	3.33	0.15	22.91**	
		Hierarchical	0.20	0.17	1.17	
		Adhocracy	0.31	0.27	1.17	
		Clan	0.63	0.20	3.15**	

Note: Model 1 constant – the reference group is Adhocracy; Model 1a constant – the reference group is Clan culture; Model 1b constant – the reference group is Market culture; p < 0.01
Source: Authors

The overall model was statistically significant (F (3,149) =3.68, p<.05), although the explained variance was modest (R^2 = .069; f^2 = .074). Employees in clan cultures reported the highest levels of satisfaction with coworkers. Significant

differences were found between clan and hierarchical cultures and between clan and market cultures. The lowest levels of coworker satisfaction were observed in market cultures. No statistically significant differences were found between hierarchical, market, and adhocracy cultures, nor between clan and adhocracy cultures. Differences in satisfaction with promotion opportunities are presented in Table 9.

Table 9: Differences in promotion satisfaction by organizational culture

Criterion		Predictors	B	S.E.	t	Model Summary
Promotion satisfaction	Model 1	Constant	3.13	0.17	18.58**	R=0.247, R^2=0.061, F(3,149)=3.23, p<0.05, f^2=0.064
		Hierarchical	-0.49	0.20	-2.44*	
		Adhocracy	0.13	0.32	0.39	
		Market	-0.51	0.25	-2.06*	
	Model 1a	Constant	2.64	0.11	24.98**	
		Adhocracy	0.61	0.29	2.07*	
		Market	-0.02	0.21	-0.10	
		Clan	0.49	0.20	2.44*	
	Model 1b	Constant	2.62	0.18	14.57**	
		Hierarchical	0.02	0.21	0.10	
		Adhocracy	0.63	0.33	1.92	
		Clan	0.51	0.25	2.06*	

Model 1 constant – the reference group is Clan culture; Model 1a constant – the reference group is Hierarchical culture; Model 1b constant – the reference group is Market culture; $p < 0.01$; $p < 0.05$
Source: Authors

The regression model was statistically significant ($F(3,149) = 3.23$, $p < .05$), explaining 6.1% of the variance ($f^2 = .064$). Employees in adhocracy cultures reported the highest satisfaction with promotion, followed by those in clan cultures, while the lowest satisfaction was observed in market cultures. Significant differences emerged between clan and hierarchical cultures and between clan and market cultures. These findings suggest that flexibility-oriented cultures are associated with more favourable perceptions of career advancement.

Results for overall job satisfaction are shown in Table 10.

Table 10: Differences in overall job satisfaction by organizational culture

Criterion		Predictors	B	S.E.	t	Model Summary
Overall job satisfaction	Model 1	Constant	3.47	0.11	31.25**	
		Adhocracy	-0.04	0.21	-0.20	
		Market	-0.38	0.16	-2.36*	
		Hierarchical	-0.33	0.13	-2.54*	
	Model 1a	Constant	3.09	0.12	26.01**	R=0.24, R^2=0.057, F(3,149)=3.02, p<0.05, f^2=0.060
		Adhocracy	0.34	0.22	1.57	
		Hierarchical	0.05	0.14	0.36	
		Clan	0.38	0.16	2.36*	
	Model 1b	Constant	3.43	0.18	18.90**	
		Hierarchical	-0.29	0.19	-1.50	
		Clan	0.04	0.21	0.20	
		Market	-0.34	0.22	-1.57	

Note: Model 1 constant – the reference group is Clan culture; Model 1a constant – the reference group is Market culture; Model 1b constant – the reference group is Adhocracy; $p < 0.01$; $p < 0.05$
Source: Authors

The model reached statistical significance ($F(3,149) = 3.02$, $p < .05$), although the explained variance remained relatively low ($R^2 = .057$; $f^2 = .060$). Employees in clan cultures reported the highest overall job satisfaction, whereas the lowest levels were found in market cultures. Significant differences were identified between clan and market cultures as well as between clan and hierarchical cultures. However, no significant differences were found between clan and adhocracy cultures, nor among the remaining pairwise comparisons.

No statistically significant differences across culture types were found for satisfaction with salary, supervisors, or the nature of work. These findings indicate that organizational culture has a statistically significant, yet small, effect on overall job satisfaction and on specific dimensions, namely satisfaction with coworkers and promotion opportunities. Employees in flexibility-oriented cultures, particularly clan cultures, tend to report higher levels of satisfaction compared to those in stability-oriented cultures (market and hierarchical). Although the detected effects are modest in magnitude, the pattern of results provides partial support for the H4 hypothesis, confirming that differences in job satisfaction exist across dominant organizational culture types, particularly under crisis conditions.

The last hypothesis H5 referred to the qualitative part of the research. The final sample of respondents consisted of 194 respondents, of whom 90 (46.4%) stated that there had been a change in organizational culture during the pandemic. Of the respondents who reported perceived changes, 41 (45.6%) additionally described the perceived changes. It is evident that

slightly less than half of the respondents stated that they perceived a change in organizational culture. In order to gain insight into which changes were most pronounced, the responses were systematized in such a way that each response was assigned a category according to the characteristics of the organizational culture. Table 11 shows data on organizational cultures and changes perceived by employees of these organizations.

Table 11: Perceived changes in organizational culture

Organizational Culture	N	Perceived Changes
Clan	9	Efficiency; Flexibility; Interpersonal relations; Communication; Business processes
Adhocracy	2	Flexibility; Interpersonal relations
Market	7	Flexibility; Interpersonal relations; Business processes; Strategic changes; Efficiency
Hierarchical	17	Flexibility; Interpersonal relations; Communication; Business processes; Strategic changes
Clan/Hierarchical	2	Flexibility; Business processes
Adhocracy/Market	1	Interpersonal relations
Adhocracy/ Hierarchical	1	Business processes
Market/Hierarchical	2	Flexibility; Interpersonal relations; Communication

Source: Authors

Existing empirical research conducted in Croatia examining organizational culture according to the typology applied in this study was mainly oriented towards individual industries. In their research, Mečev and Grubišić (2020) confirmed that the ICT industry has the highest percentage of hierarchical cultures, while Šmider and Petrl Balog (2012) state that clan culture was the most prevalent in libraries. Suša Vugec (2020), in her doctoral dissertation, examined organizational culture in 71 companies with more than 50 employees from different industries and found that market and hierarchical culture types were equally dominant. The relationship between organizational culture types and overall job satisfaction obtained in this study is in line with the findings of El Badawy et al. (2016), who found a positive relationship between all culture types and overall job satisfaction, with the highest relationship between clan culture and adhocracy, a result also obtained in this research. The results obtained indicate that the more elements of clan culture and adhocracy in organizations, the higher the overall job satisfaction, with the level of connection being higher in clan culture than in adhocracy. In clan culture, great emphasis is placed on people and interpersonal relationships, which is a possible explanation for the highest correlation between clan culture and satisfaction with superiors and coworkers. If we look at this result in the context

of the pandemic, which represents not only a financial crisis but also a health crisis, it is not surprising that the highest satisfaction was measured in clan culture, given that this culture has an internal focus and orientation towards interpersonal relationships. Furthermore, the research results confirmed that flexibility is a significant predictor of overall job satisfaction and that the effect of flexibility on overall employee satisfaction is large. This result indicates that flexibility plays a significant role in explaining overall employee satisfaction. The same result was obtained for individual dimensions of job satisfaction where flexibility also plays a significant role. This is in line with existing research showing that flexible organizations adapt to changes more easily and cope better during times of crisis (Deverell & Olsson Gardell, 2010; Azanza et al. 2013). Moreover, the results suggest that flexibility could play a key role in job satisfaction during a pandemic, given that clan culture and adhocracy fall on the flexibility side of the structural dimension, while market and hierarchical cultures lie on the opposite, stability-oriented side of the dimension.

5 Conclusions

The COVID-19 pandemic has brought new challenges to organizations and has forced them to make necessary changes in order to maintain business, which in some organizations also affected the organizational culture. This opened up new research questions. This paper tried to provide answers to some of them and contribute to the understanding of the processes that took place in organizations, emphasizing organizational culture and job satisfaction. The results of this research indicated the importance of flexibility as a dimension of organizational culture and the role it plays in explaining job satisfaction. This research showed that employees in organizations with a flexible culture report higher levels of job satisfaction. The results of this research can help organizations and managers understand the role that organizational culture plays in employee job satisfaction. When introducing changes to organizational culture, managers should increase flexibility, and when shaping new cultures, they should go in the direction of developing one of these two types of culture, this is, they should strive for flexible organizational design. It was also found that employees are the least satisfied with promotion opportunities, and it is on this dimension of satisfaction that flexibility has the strongest effect of all dimensions of job satisfaction. Therefore, the introduction of clearer, fairer criteria and a promotion system could lead to greater employee satisfaction, and thus increase the overall level of satisfaction. Although changes in organizational culture were perceived, it is not known whether these changes are an immediate reaction of organizations to the situation and whether they will lead to long-term changes in organizational culture, so future research could provide answers to these questions. The main limitation of this paper is the correlational research design, which prevents conclusions from being drawn about cause-and-effect relationships. Therefore, future research should focus more on longitudinal research design that could compare organizational culture during the pandemic and post-pandemic times in order to examine how the pandemic affected culture, as well as employee satisfaction. Future research could also extend the model by incorporating additional outcome variables. For example, researchers could use sustainable value added (Miljenović,

2018) as an integrative performance metric to capture sustainability-related implications alongside job satisfaction elements, enabling an assessment of whether organizational culture and job satisfaction in a crisis context translate into longer-term socio-environmental performance. The conducted qualitative research did not cover in-depth interviews, which is another recommendation for future research.

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Part IV: Economic Efficiency, Sustainability and Social Factors

Institutional Biases and the Gender Pay Gap: Management Challenges in Croatian Higher Education: Evidence from the University of Rijeka

Original scientific paper

Ana Marija Sikirić Simčić[1], Aleksandar Đukić[2], Elisa Bellesi[3]

ABSTRACT

Croatia ranks 24th on the EU Gender Equality Index 2024, receiving 59.7 points out of 100. This score is 11.5 points below the EU average, indicating that Croatia continues to lag significantly behind other EU countries in gender equality. Universities are expected to lead by example in promoting gender equality. The University of Rijeka was the first Croatian university to adopt a Gender Equality Plan (2021–2025) and in 2021, established a Gender Equality Council. These initiatives focus on promoting equal opportunities in decision-making, research, and teaching, as well as balancing professional and personal life. This paper examines the gender pay gap based on salary data collected in 2023 for faculty and staff. Despite strict legislation governing academic salaries in Croatia, the findings indicate that a pay gap nonetheless exists. The causes include occupational and vertical segregation, career breaks due to family obligations, and institutional biases. The study highlights the importance of recognizing and addressing these inequalities to promote fairness in academic advancement and salary policies. The proactive measures at the University of Rijeka not only highlight existing disparities within the institution but also present it as a model for other Croatian universities aiming to reduce gender pay gaps and foster an inclusive academic environment.

Keywords: *Gender pay gap, University of Rijeka, Gender equality, Institutional policies*

JEL classification: *J16, J71, J24, I24*

1 *Associate Professor, University or Rijeka, Faculty of Economics and Business, Ivana Filipovića 4, 51000, Rijeka, Croatia. Phone: +38551355120. E-mail: ana.marija.sikiric@efri.uniri.hr.*

2 *Doctoral student, University or Rijeka, Faculty of Economics and Business, Ivana Filipovića 4, 51000, Rijeka, Croatia. Phone: +38551651116. E-mail: aleksandar.dukic@medri.uniri.hr.*

3 *Teaching Assistant, University or Rijeka, Faculty of Economics and Business, Ivana Filipovića 4, 51000, Rijeka, Croatia. Phone: +38551355184. E-mail: elisa.bellesi@efri.uniri.hr.*

1 Introduction

Croatia achieved a score of 59.7 out of 100 on the Gender Equality Index 2024, positioning it 11.3 points below the European Union (EU) average and ranking 24th among the 27 EU member states. Notably, Croatia dropped four places compared to the previous edition of the Index, reflecting a relative decline in its gender equality performance. Since 2021, Croatia's overall score has decreased by one point, with the decline primarily driven by a significant deterioration in the core domain of power (−5.3 points). Despite these recent setbacks, the long-term trend in Croatia remains positive: since 2010, the country's overall Index score has increased by 7.4 points, mainly due to substantial improvements in the core domain of power, with smaller gains observed in other core domains (EIGE, 2024). Both the Index value and Croatia's ranking relative to other EU countries are robust indicators of where Croatia stands within the EU on gender equality.

From an economic perspective, gender inequality is typically measured by the position of women in the labour market. Statistical data from the Croatian Bureau of Statistics (CBS, 2024) indicate that women in Croatia remain in a disadvantaged position, despite making up a larger share of the highly educated workforce. This disadvantage is reflected in lower rates of economic activity, lower employment rates, and lower earnings among women compared to their male counterparts. Despite EU policies and strategies aimed at achieving gender equality in earnings between women and men, the gender pay gap continues to persist. Factors contributing to this gap include gender stereotypes in social and professional roles, a gender-segregated labour market, unequal labour participation, and barriers to entering certain occupations. This situation represents a complex issue, with notable differences between countries and economies (Leythienne & Perez-Julian, 2021). In Croatia, the income gap between men and women, known as the gender pay gap, amounted to 9.8 percentage points on a monthly basis in 2022, according to CBS (2024) data.

When comparing the gender pay gap in Croatia with the EU average, Croatia's gap is lower. Specifically, according to Eurostat data based on gross hourly earnings, Croatia's gender pay gap stood at 7.2 % in 2022 and increased slightly to 7.4 % in 2023, while the EU average was 12.2% in 2022 and 12% in 2023 (Eurostat, 2025a). Across EU countries, the gender pay gap ranged from -0.9% in Luxembourg to 19.0% in Latvia, a difference of 20 percentage points. A negative gender pay gap means that, on average, women's gross hourly earnings are higher than those of men. The lower gender pay gap observed in Croatia is probably due to selection bias, especially since the employment rate is lower for women than for men: women engaged in the labour market may have comparatively higher skills and education levels than men, so their average salary is not much lower than that of a larger pool of working men with diverse education and skill levels. Therefore, income disparities between men and women are most pronounced in so-called "female-dominated" sectors, where women make up more than 65% of employees, and less pronounced in "male-dominated" sectors. For example, in the construction sector in Croatia, where women constitute only 10.4% of the workforce, the gender pay gap is negative (-7.6 percentage points), meaning that women even earn higher incomes than men in this sector. Conversely, in financial and insurance

activities, where women represent more than 68% of employees, the gender pay gap reaches 29.9 percentage points (CBS, 2024)

The gender pay gap is generally much lower for new labour market entrants and tends to widen with age. This phenomenon is largely attributed to women experiencing career interruptions throughout their working lives. For example, in Croatia, the gender pay gap is highest among the 45-54 age group, where it reaches 11.4%. Moreover, in 2023, almost all EU countries recorded a higher gender pay gap (in absolute terms) in the private sector than in the public sector. In the case of Croatia, the gender pay gap in the public sector in 2023 was 5%, whereas in the private sector it was 13.4% (Eurostat, 2025Ha). This difference might be explained by the fact that, in most EU countries, public sector pay is determined by transparent wage grids that apply equally to men and women.

Public university faculties are an especially relevant group for examining gender pay gaps. Higher education and research institutions (universities) play a central role in advancing gender equality. They do so not only through their teaching and research activities but also through their internal structures, policies, and pay practices. Increasingly, universities recognize the need to promote gender equality across both academic and non-academic domains, aiming to foster fair treatment, equal opportunities, and an inclusive work environment. Therefore, the aim of this paper is to determine the gender pay gap among faculty and non-faculty staff at the public University of Rijeka. The University of Rijeka actively promotes gender equality through a variety of initiatives and measures. Notably, it is the first university in Croatia to establish its own Gender Equality Plan (GEP), adopted by the University Senate in May 2021. According to the newly published Times Higher Education Impact Rankings 2025, the University of Rijeka is ranked 37th out of 1,559 universities from 119 countries in the Gender Equality category (Sustainable Development Goal 5). This recognition highlights the university's meaningful contribution to society through education, research, and broader initiatives that promote positive changes within the community.

According to the data and literature, despite meaningful progress, gender pay gaps remain a challenge at universities worldwide. Analyses frequently show that women earn less than men, even when performing comparable roles. Faculty positions offer particularly clear insight for studying such disparities. Pay scales at public universities are typically set by formal administrative frameworks, which makes overt discrimination less visible. At the same time, the relative homogeneity of faculties in terms of education, occupation, and professional activity reduces differences attributable to other factors. These circumstances provide a clearer examination of the influence of gender on earnings. Ultimately, observed differences often reflect vertical segregation among academic ranks, a phenomenon commonly described as the "glass ceiling" effect (Hernández, 2024; Chen & Crown, 2019).

2 Literature review

2.1 Gender pay gap in academia

Although numerous countries have invested substantial effort in developing gender equality policies to ensure equal treatment of men and women in the academic labour market (Salinas and Bagni, 2017), persistent pay disparities between male and female faculty continue to be documented (European Commission, 2025; Gamage et al., 2024). Investigations into salary differences within academia trace back to the early 1970s, initially driven by legal and institutional reforms in higher education (Blau & Kahn, 1999). Since then, extensive literature has emerged analysing the gender pay gap, with comprehensive reviews such as Blau and Kahn (2017) highlighting sectoral and occupational segregation and motherhood-related penalties as primary explanatory factors. Women are often underrepresented in higher-paying fields like engineering and computer science and overrepresented in lower-paying fields such as the humanities and social sciences. Another aspect is vertical segregation, as women are less likely to hold senior academic and management positions (Gordon et al., 2024; Humphries, 2023). An additional contributing factor to slower promotion rates is the disproportionate caregiving responsibilities undertaken by female academics during tenure-track years, leading to less competitive research portfolios, which is particularly pronounced among academics with children (Mason & Goulden, 2002). Women take career breaks or work part-time due to family commitments, which affects their career progression and salary (Gordon et al, 2024; Humphries, 2023). This discrepancy persists even after accounting for various factors, including experience and department (Chen & Crown, 2019).

Rosa and Clavero (2021) highlight the transformative potential of higher education and research as instruments of empowerment and social change. Consequently, universities play a vital role in fostering gender equality, diversity, and inclusion not only within academic environments but also in broader society. Despite the regulated pay-setting procedures, increased transparency, well-defined promotion pathways, and flexible working arrangements typical of academia, gender pay inequalities endure. The lower earnings of female researchers early in their careers contribute to the “leaky pipeline” phenomenon, whereby fewer women attain senior positions associated with higher remuneration (Dynan & Rouse, 1997; Ginther & Kahn, 2004; Hatch, 2017; Kahn, 1993; McDowell et al., 1999, 2001).

Promotion decisions ideally rest on objective performance indicators across teaching, research, and service. Yet, evidence reveals that implicit biases influence evaluative processes, perpetuating gender disparities in career advancement. Explanations for gender pay disparities in academic settings often highlight disproportionate teaching loads among women in addition to their greater involvement in administrative and pastoral care responsibilities as duties that are frequently associated with limited prospects for career advancement (El-Alayli et al., 2018; O’Meara et al., 2017; Guarino & Borden, 2017; Babcock et al., 2017). Experimental research demonstrates that student biases result in lower course evaluation ratings for women instructors compared to their male counterparts (MacNell et al., 2015; Boring, 2017).

Moreover, gender bias permeates the peer-review process, with female-authored manuscripts experiencing longer review durations and heightened scrutiny despite superior readability metrics (Hengel, 2017; Brower and James, 2023). Rabovsky and Lee (2018) further observe that reliance on public funding correlates with narrower gender wage gaps, whereas dependence on competitive research funding is associated with wider pay disparities.

Contributing to career advancement bias is the lower likelihood of women applying for academic positions (Nielsen, 2016; Ceci et al., 2014), societal perceptions framing women as more conscientious yet compliant (Eswaran, 2014), and typically diminished willingness to engage in competitive behaviours (Buser et al., 2014; Booth et al., 2019; Nicholls, 2022). By contrast, men, often characterized as assertive and ambitious “alpha males”, tend to rate and cite their scholarly work more favourably (Coate & Howson, 2016; King et al., 2017). Women who emulate such assertiveness may face negative stereotypes, such as being labelled “aggressive” (Monroe, 2013). Consequently, women publish less frequently than men (Bird, 2011), undergo longer peer-review processes (Branch & Kvasnicka, 2017), have less access to mentorship (Buch et al., 2011), and also encounter more stringent standards in prestigious journals (Hengel, 2017). Male academics are more likely to acquire markers of academic prestige, which are vital for career progression, perpetuating slower, less frequent promotions among women (Coate & Howson, 2016; Winslow & Davis, 2016). Collectively, these findings illustrate how entrenched gendered cultural norms and structural biases systematically hinder women from gaining recognition and achieving career trajectories in academia, sustaining persistent inequalities in professional outcomes (Harris et al., 2023).

2.2 Addressing gender pay gaps in academia

While significant progress has been made in recent years, universities must continue implementing proactive policies and practices to close the gender gap and ensure equitable opportunities for all employees, regardless of gender. By cultivating an inclusive and fair environment, universities can assume a leadership role in advancing gender equality both within academia and in society at large. One increasingly prominent mechanism in addressing gender inequalities in higher education is the implementation of Gender Equality Plans (GEPs). These plans cover a broad range of thematic areas, such as recruitment, selection, career progression, work-life balance, leadership and decision-making, organizational culture, gender in research and educational practice, and measures for combating gender-related harassment and assault, all tailored to institutional contexts and needs (Rosa & Clavero, 2021). However, GEPs have faced criticism for their predominantly instrumental rationale, which emphasizes efficiency, and for their reliance on conservative frameworks that shape conceptualizations of gender equality and the corresponding interventions (Lätti, 2017). Moreover, questions remain regarding the capacity of GEP initiatives to adapt effectively to contemporary transformations in the higher education sector, including corporatization, marketization, and globalization (Rosa & Clavero, 2021).

A recurrent policy designed to mitigate the motherhood penalty in academia involves granting faculty members an additional year of eligibility prior to tenure evaluation. Some institutions restrict this extension solely to female faculty members, whereas others adopt gender-neutral policies that permit both men and women with children to benefit. Despite intentions to reduce childcare-related disparities and the stigma associated with leave, emerging evidence indicates that these gender-neutral policies may inadvertently disadvantage women, as men frequently utilize the extended time to enhance research productivity, thereby potentially elevating the benchmarks necessary for women to obtain tenure (Antecol et al., 2018). This phenomenon increases the inherent difficulties in devising effective interventions that support academic mothers without worsening existing gender inequities.

Mentoring programs, supported by numerous organizations, play an instrumental role in fostering the success of underrepresented groups by providing guidance, expanding professional networks, and improving career prospects. Empirical studies reveal that female doctoral students in STEM disciplines who are mentored by female advisors tend to achieve higher publication rates (Pezzoni et al., 2016; Guale & Piacentini, 2017). Furthermore, mentoring initiatives in economics have been linked to increased publication outputs and increased grant funding among women scholars (Blau et al., 2010). Such programs facilitate the transfer of tacit knowledge and the development of collaborative networks, which is particularly significant given that female academics often engage in more intensive collaboration with fewer coauthors (Ductor et al., 2018; Ductor, 2015). Consequently, mentoring constitutes a critical mechanism for increasing research productivity and academic advancement among women.

To address persistent gender imbalances, additional measures should focus on increasing the participation of both women and men in fields where women are underrepresented, thereby promoting a more balanced workforce within the sector. Expanding female representation in traditionally male-dominated disciplines and on tenure evaluation committees may help reduce promotion disparities by providing mentorship and support to female students, thus mitigating the leaky pipeline phenomenon (Hale & Regev, 2014; Bostwick & Weinberg, 2022). While augmenting the presence of women on promotion committees might not yield in itself substantial increases in the promotion of women, elevating them to leadership positions such as presidents and senior administrators has been correlated with greater recruitment of female faculty members (Bagues et al., 2017; Ehrenberg et al., 2012).

At policy level, various governments employ pay transparency initiatives to combat gender pay inequities. On a broader scale, greater pay transparency, anticipated to be implemented across European nations following the European Union's Pay Transparency Directive of 2023, holds promise in narrowing the gender pay gap through more rigorous enforcement of equal pay principles (Magda et al., 2025). Beyond monetary considerations, it remains a critical endeavour to identify the non-monetary factors that facilitate the retention of women and their career progression in academia. Addressing entrenched stereotypes and biases tied to gender norms represents a significant frontier for advancing gender equality in higher education.

3 Gender equality initiatives at the University of Rijeka

The University of Rijeka has established itself as a national leader in promoting gender equality within Croatian higher education by incorporating pioneering institutional structures and strategic planning. As a trailblazer in this field, the University of Rijeka was the first university in Croatia to adopt its own Gender Equality Plan for the period 2021–2025 and is currently in the process of preparing the Gender Equality Plan 2030. The Gender Equality Plan defines four key strategic areas for the 2021–2025 period: promoting gender equality in decision-making processes; strengthening gender equality in scientific research and career development; integrating gender perspectives into teaching and academic training; and improving work–life balance to support both personal and professional commitments. These strategic areas reflect the University's comprehensive approach to embedding gender equality across all levels of institutional activity.

As a direct outcome of the Gender Equality Plan, the University established the Gender Equality Council in July 2021, marking another first among Croatian universities. The Gender Equality Council serves as a representative body, and it plays a central role in advancing and overseeing gender equality within the institution. It monitors the implementation of the Gender Equality Plan and ensures progress toward its strategic objectives. Acknowledging that the Croatian language is often not gender-sensitive and tends to render women invisible in everyday, formal and official discourse, the Council has developed specific guidelines for gender-sensitive communication across the University. Recognizing that balancing work and family responsibilities is a significant challenge for many employees, particularly women, the Council has also introduced targeted guidelines to support academic and administrative staff in achieving work–life balance in both teaching and research activities. In an endeavour to complement these aspects, the University opened a campus childcare facility in cooperation with the City of Rijeka, further supporting work–life harmony.

The Council actively highlights and rewards institutional, student and staff initiatives that promote gender equality, thereby fostering a culture of recognition and encouragement that further strengthens the institution's commitment to gender equality as a core value. It also addresses issues related to gender-based violence within the university community and supports research on gender equality patterns and outcomes.

In addition, the University actively promotes age-friendly initiatives, systematically integrates a gender perspective into research and curricula, and continually works to improve accessibility for persons with disabilities, in line with its document "Guidelines for Ensuring and Improving Quality: Diversity and Inclusion."

A crucial component of the University's Gender Equality Plan is the systematic implementation of institutional research and the collection of both quantitative and qualitative data on gender equality indicators. This evidence-based approach enables the University to monitor progress, identify areas for improvement and make informed policy decisions. For example, one of the research strands has focused on gendered patterns of international staff and

faculty mobility. In 2023, the Gender Equality Council collected comprehensive salary data for both academic and administrative staff to identify potential gender pay gaps across the institution and within specific university units, representing a critical step toward understanding and addressing systemic inequalities.

Through these multifaceted initiatives and institutional commitments, the University of Rijeka demonstrates a comprehensive, evidence-based approach to advancing gender equality, not only within higher education but also as a model for promoting broader societal progress.

4 Pay structure in higher education in Croatia

The calculation of salaries at public higher education institutions in the Republic of Croatia is governed by a comprehensive legal framework. The Labour Act (OG 93/14, 127/17, 98/19, 151/22, 46/23, 64/23) stipulates that salaries in employment contracts be set in gross amounts, while the methodology for calculating salaries is further regulated by the Act on Salaries in the State Administration and Public Services (OG 155/23), the Regulation on Job Titles, Conditions for Assignment, and Salary Coefficients for Salary Calculation in Public Services (OG 22/2024), and the Decision on the Base Salary for Public Service Salary Calculation in 2025 (OG 155/24). Additionally, the Basic Collective Agreement for Public Service Employees and the Collective Agreement for Science and Higher Education provide essential supplementary regulations. Relevant to institutions under the Ministry of Science, Education, and Youth are the Regulation on Criteria and Methods for Using Non-Specific Donations and Own Revenues, and the Regulation on Criteria and Methods for Using Designated Revenues of Budget Users (both OG 79/2024).

The Labour Act defines salary as compensation paid by the employer to the employee for work performed within a calendar month, based on prescribed, determined, or mutually agreed criteria set forth in laws, collective agreements, workplace regulations, or employment contracts. Importantly, the Act requires equal pay for equal work or work of equal value between male and female employees. Equal work is understood as work performed by two persons of different genders where the tasks, conditions, and capabilities required are the same or sufficiently comparable, allowing them to substitute for each other. Differences in isolated aspects of the work or working conditions do not negate the equivalence of the work as a whole. Work of equal value is determined based on objective criteria, including the qualifications obtained through education, knowledge, skills, responsibility, independence, and the conditions under which the work is performed.

In public service job positions, salary is calculated by multiplying the complexity coefficient of the job position by the base salary applied for salary calculation. This amount is further increased by 0.5% for each year of completed work experience, regardless of whether the employee works full-time or part-time.

Furthermore, employees at higher education institutions who contribute to generating their own or designated income are entitled to additional salary increases. Various supplements may also be granted alongside base salaries,

such as allowances for living separately from the workplace, fieldwork, overtime, and other specific conditions. Despite the clear legislative framework regulating salary calculations at public institutions, a gender pay gap persists within the sector.

5 Methodology and data

The unadjusted or uncontrolled gender pay gap measures the average difference in pay between men and women. While the adjusted or controlled pay gap, by contrast, controls for factors like job role, education, and experience to isolate other influences. In this study, authors applied the standard formula for calculating the unadjusted gender pay gap both at the University level and within each University unit. Specifically, the gender pay gap is expressed as the difference between the average salaries of male and female employees, divided by the average male salary:

$$Genderpaygap = \frac{averagemalesalary - averagefemalesalary}{averagemalesalary} x100 \quad (1)$$

The use of the unadjusted gender pay gap is justified by its ability to give a broad view of gender pay disparities, even though it does not capture nuanced factors like individual characteristics or discrimination. This approach ensures methodological consistency and comparability across organizational levels and staff categories (Dupuy et al., 2009). Given the relative homogeneity within faculties, where education levels, occupational profiles, and professional activities align closely, the unadjusted gap effectively minimizes confounding from other factors. It thus provides a valid lens for examining gender's direct impact on earnings disparities. Observed gaps primarily reflect vertical gender segregation across academic ranks, signalling structural barriers that hinder women's advancement to higher positions or hierarchical levels or their involvement in lucrative projects. This raw measure highlights institutional patterns warranting targeted interventions, beyond what controlled analyses might reveal.

Data on average gross monthly income for women and men at each university unit were collected with the support of the Gender Equality Council and Accounting Offices. The averages are based on salaries for the year 2023, regardless of payment date. Specifically, salaries for December 2023, paid in January 2024, were included, while salaries paid in January 2023, relating to December 2022, were excluded. The calculation considers base salaries from the Ministry of Science and Education, plus all additional payments such as wage differences, bonuses, performance awards, and compensation for teaching in part-time or postgraduate programs.

Gross salary was used in this analysis instead of net salary because net pay is subject to a variety of factors unrelated to pay equity, such as place of residence, dependents, and number of children, which are often affected by tax policies. These factors can introduce distortions into the measurement of the gender pay gap. Although prior research indicates that the presence of children in the household tends to widen the gender pay gap, this effect cannot

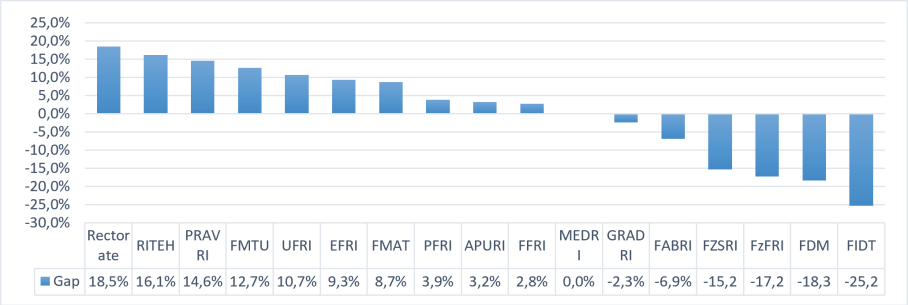
be reliably detected using net salary data due to the unknown distribution of tax reliefs among parents or guardians. Employing gross salary as the basis for analysis ensures that the calculated gender pay gap accurately reflects wage disparities independent of taxation and social benefit structures, thereby encompassing all relevant components of employee remuneration. This methodological choice strengthens the validity of findings by isolating genuine compensation differences attributable to gender.

6 Results and discussion

An analysis of staff composition at the University of Rijeka in 2023 shows that women form the majority in both teaching and non-teaching roles, accounting for 58.3% of teaching staff and 75.5% of non-teaching staff. Notably, across all organizational units, women account for more than 50% of non-teaching staff. Regarding teaching staff, there are two organizational units, the Faculty of Maritime Studies (PFRI) and the Faculty of Engineering (RITEH), that indicate a significant male majority. Nevertheless, a predominance of women does not guarantee pay equality. On average, women earn 2.9% less than men among teaching staff, with the gap increasing to 12.7% among non-teaching staff. The higher gender pay gap among non-teaching staff is not unexpected, as evidence shows that the gender pay gap is often more pronounced in so-called female-dominated professions, and other factors contributing to the gender pay gap are likely to have a stronger impact in this group, which is also less homogeneous (CBS, 2024).

Gender pay gaps among teaching staff demonstrate notable variation across organizational units, even as the overall university-level difference remains modest (Figure 1). For teaching staff, pay gaps range from a maximum of 18.5% at the Rectorate, where men earn significantly more, to a minimum of -25.2% at the Faculty of Informatics and Digital Technologies (FIDT), where women out-earn men on average. It is important to note that these values represent both positive and negative pay gaps; the negative gender pay gap is not “low”, but rather signifies that women, on average, earn more than men in those units. Out of the seventeen analysed organizational units, only six report a negative gender pay gap, while substantial positive gaps in favour of men persist at the Rectorate (18.5%), Faculty of Engineering (RITEH, 16.1%), and Faculty of Law (PRAVRI, 14.6%).

Figure 1: Gender pay gap among teaching staff by organizational unit at the University of Rijeka, 2023 (in %)



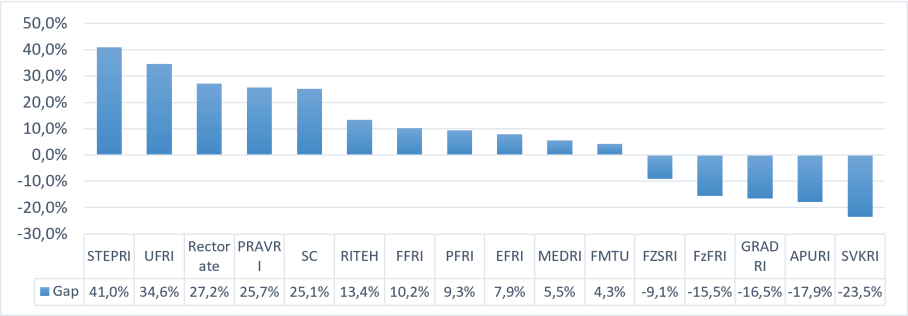
Source: Authors

Data show that these disparities exist independently of gender composition. For example, the Faculty of Engineering (RITEH) has only 23% women among its teaching staff but exhibits a 16.1% gap in favour of men. In contrast, the Faculty of Law (PRAVRI) is over 70% female, yet men still enjoy a 14.6% pay advantage. These findings suggest that gender parity in numbers is not sufficient to achieve pay equity and that structural and contextual factors at the unit level strongly shape pay outcomes.

Negative pay gaps (where women earn more than men) are found especially in units with a notable share of part-time associates, often with probably women working full-time and men holding concurrent, part-time positions across institutions (for example, the Faculty of Dental Medicine – FDM). This employment pattern can lead to lower average earnings for men at these units, contributing to the observed gap in favour of women. Therefore, interpreting pay gap data requires consideration of type of employment and workload distribution.

A similarly diverse pattern is observed among non-teaching staff (Figure 2). For example, the Science and Technology Park of the University of Rijeka (STEPRI), with a gender pay gap of 41%, and the Faculty of Teacher Education (UFRI), with a gap of 34.6%, show pronounced disparities in favour of men. Other units with notable positive pay gaps include the Rectorate (27.2%), Faculty of Law (25.7%), and Student Centre (25.1%). Conversely, gaps favouring women are evident in five units, such as the University Library (SVKRI, -23.5%) and the Academy of Applied Arts (APURI, -17.9%), among others. In four organizational units, a gender pay gap could not be calculated because 100% of the non-teaching staff are female employees. Once again, these results demonstrate that the gender pay gap cannot be explained solely by the gender composition of employees, suggesting that in this group persistent pay inequalities may be linked to differences in job rank, contract type, or specific institutional practices.

Figure 2: Gender pay gap among non-teaching staff by organizational unit at the University of Rijeka, 2023 (in %)



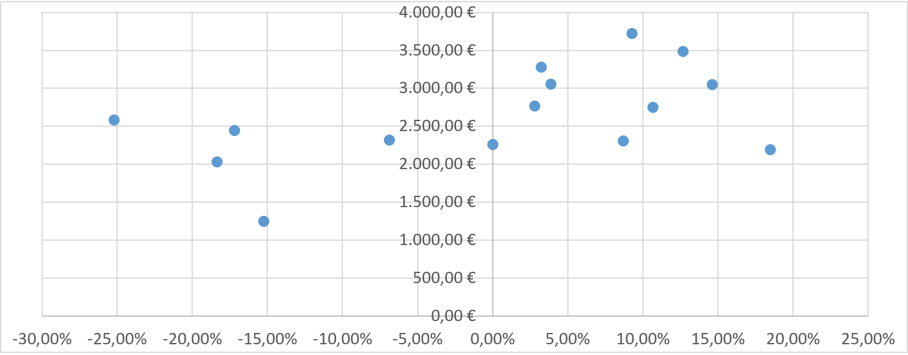
Source: Authors

In addition to differences in the gender pay gap across university units, the data reveal substantial variation in average salary levels among teaching staff. These differences are likely driven by several factors, including the distribution of academic ranks (with higher ranks earning greater salaries), the proportion of employees working part-time (often associated with lower earnings), and the prevalence of salary supplements resulting from participation in market-oriented projects, EU-funded projects, and similar activities. Such salary supplements may further contribute to pay disparities, especially if women are less involved in these income-raising activities.

Based on data collected in 2022 by the Gender Equality Council, analysis of gender balance in project leadership across different types of projects shows that women comprise 61% of all scientific, artistic, and teaching staff who are eligible to lead projects. Nevertheless, actual female participation in project leadership roles stands at only 50%, indicating that men are proportionally more likely to occupy these positions. Notably, women remain underrepresented in market-oriented projects (33%) and EU-funded projects (46%), which are particularly important for generating additional income.

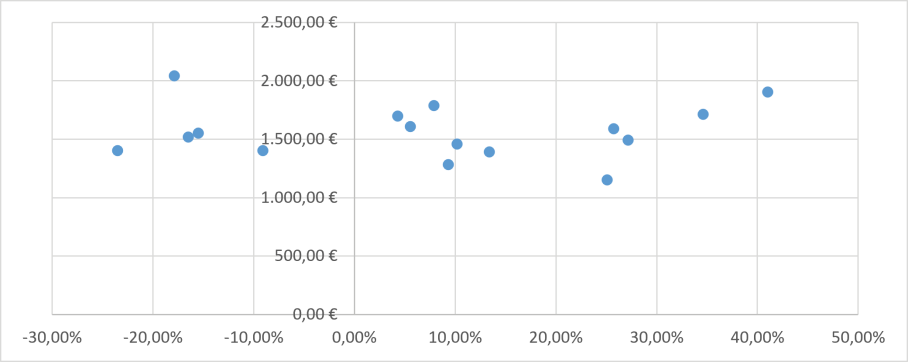
Figure 3 and Figure 4 provide deeper insight by plotting the relationship between the gender pay gap and average salary levels for both teaching and non-teaching staff across organizational units at the University of Rijeka. Each data point represents a distinct unit, positioned according to its pay gap (horizontal axis) and average monthly salary (vertical axis), enabling simultaneous comparison of both metrics.

Figure 3: Relationship between gender pay gap and average salary levels among teaching staff by organizational unit, University of Rijeka, in 2023



Source: Authors

Figure 4: Relationship between gender pay gap and average salary levels among non-teaching staff by organizational unit, University of Rijeka, in 2023



Source: Authors

Figures 3 and 4 demonstrate that average salary levels do not systematically predict the direction or magnitude of the gender pay gap. According to Figure 3, all units with average incomes above €2,700 exhibit a positive gender pay gap, yet pronounced or even larger gaps are also present at lower salary levels. The results of the Pearson correlation coefficient indicate a moderate positive correlation between average income and the gender pay gap; however, this relationship is not statistically significant at the conventional level ($p < 0.05$). The observed result suggests a possible trend, but it is not strong enough to support a reliable association in the sample (Pearson = 0.4744, $p = 0.0544$). This means that higher salaries may create greater potential for a gender pay gap, but such gaps also occur at lower income levels and are not exclusively limited to higher earnings. In contrast, for non-teaching staff, the calculated correlation coefficient is statistically insignificant and does not indicate any

relationship between these variables (Pearson = 0.0277, p = 0.9188).

Taken together, these analyses reveal strong heterogeneity in salary disparities, indicating that there is no general rule or statistically significant correlation between the proportion of women and the magnitude of the gender pay gap. Instead, pay outcomes are shaped by a complex interplay of unit-specific factors, including contract type, academic rank, employment arrangements, workload distribution, participation in supplementary income activities, and promotion practices. The gap between eligibility and actual leadership highlights the importance of examining institutional practices and structural factors that may limit opportunities for women to lead lucrative projects.

To clarify at a conceptual level, structural factors operate at the macro-societal scale, embedding persistent gender inequalities through broad labour market patterns. These include occupational segregation (where women remain concentrated in lower-paying fields like humanities despite identical wage rules across disciplines), vertical segregation (the “glass ceiling” blocking access to senior roles), and motherhood penalties such as career breaks, part-time work, or reduced research output due to family responsibilities, all cumulatively widening pay gaps over time. In contrast, institutional factors emerge within specific organizations like universities through internal mechanisms and processes. Examples encompass implicit biases in promotion evaluations (e.g., disproportionate teaching/administrative loads for women, stricter peer-review scrutiny for female-authored work), unequal access to supplementary income (e.g., fewer women leading market-oriented or EU projects despite eligibility), and workload distortions from contract types or multi-institutional part-time roles.

At the University of Rijeka, structural factors explain larger pay gaps in male-dominated units like Engineering (16.1%) despite fixed regulatory wage grids, while institutional factors account for variations like the Rectorate’s 18.5% gap tied to rank distributions and project leadership disparities. This distinction shows that observed pay differences go beyond simple gender composition or average earnings, reflecting intertwined societal norms and organizational practices. Addressing them thus requires unit-level analysis, targeted interventions like bias training and transparent advancement criteria, systematic monitoring, and qualitative research into local dynamics.

In summary, while the University of Rijeka as a whole records a modest gender pay gap among teaching staff, substantial differences across faculties highlight the need for specific interventions and further investigation into the drivers of institutional pay disparities.

7 Conclusions

Although it is sometimes assumed that there is little room for a gender pay gap in public universities due to strictly regulated pay scales and legal principles of equality, the evidence shows that substantial differences in earnings between men and women still exist. While the gender pay gap in the public sector is usually smaller than in the private sector, it nevertheless persists, even

in an environment where meritocracy should ideally be the sole criterion for advancement. This is why gender equality is increasingly coming into focus within the academic community, not only in internal policies but also through curriculum development and scientific research.

The University of Rijeka stands out for its wide range of initiatives and activities designed to promote gender equality among its staff, students, and the wider community. This commitment is reflected in its international recognition, most notably, its ranking of 37th in the world in the Times Higher Education Impact Rankings for Gender Equality (SDG 5). Such recognition is the result of years of dedicated and systematic work tackling gender inequalities. The University of Rijeka was the first in Croatia to adopt a Gender Equality Plan and to establish a Gender Equality Council. As a core component of the Plan, the Council initiated systematic data collection on earnings by gender to identify potential disparities.

Analysis reveals that the gender pay gap among teaching staff at the University is, on average, quite low (2.9%), but it is much higher among non-teaching staff (over 12%). There are also significant differences between individual faculties at the University, i.e., some gaps favouring women and others favouring men, depending on the faculty. The causes of these differences are not necessarily related to staff gender composition or average earnings, but rather the specific characteristics of each field and institution. It is therefore essential to continuously collect and analyse data. Besides average monthly earnings, future analysis should also take into account actual hours worked to avoid bias related to part-time or multi-institutional employment.

Recommendations for narrowing the gender pay gap at the University of Rijeka include:

- Systematic monitoring and transparent reporting on the gender pay gap across all faculties and staff categories, including hourly wage comparisons.
- Mandatory gender mapping and analysis in all internally generated advancement criteria, especially with regard to project leadership and participation in income-generating activities.
- Investigation and identification of factors responsible for gaps above 5% at faculty level, such as vertical segregation, motherhood penalty, restricted access to project leadership or income-generating activities, or an underrepresentation of a particular gender in certain fields.
- Focused efforts to fairly recognize and distribute so-called “invisible work”, i.e., administrative, mentoring, or support roles that are essential to the system’s operation but often underappreciated and unrewarded.
- Continued improvement of training and mentoring programs that help remove obstacles to equitable advancement and participation of both women and men in all forms of recognized work.

Addressing the gender pay gap is a long-term process, with positive effects often emerging only over years of implementing gender equality. Success depends on transparency, systematic monitoring, targeted removal of specific

barriers, and the building of a culture in which equal achievement yields equal reward.

The key limitations of the study are the use of an unadjusted gap formula, which provides descriptive insights but lacks decomposition into explained (rank, experience) and unexplained (bias) components, an approach suitable for Croatia's fixed-salary system yet limiting for causal inference. Gross monthly salaries exclude hours worked, part-time effects, and productivity metrics, while 2023 snapshot data covers only Rijeka without title-level granularity or national benchmarks. Future research should employ longitudinal data across Croatian universities and qualitative analyses of unit-specific drivers to track gap trends over time. Studies should also calculate hourly earnings to account for part-time work and multi-institutional employment, while monitoring the leaky pipeline effect.

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The Impact of Informal Caregiving on Work Ability: Work Ability Survey

Original scientific paper

Sara Ražman[1], Petra Došenović Bonča[2], Mojca Bavdaž[3], Tjaša Redek[4], Nina Ponikvar[5]

ABSTRACT

Informal caregiving represents an increasingly important social and economic phenomenon that may influence individuals' health, well-being, and participation in the labour market. This paper investigates how caregiving status is linked to individual's work ability. The empirical analysis draws on data from the Work Ability Survey 2025, a nationally representative survey of the Slovenian working-age population. Work ability was measured using the internationally established Work Ability Index (WAI), which conceptualises work ability as a composite of seven interrelated dimensions reflecting both health and functional capacity. These dimensions capture current work ability compared to lifetime best, work ability in relation to physical and mental job demands, the number of diagnosed diseases, the degree of work impairment due to illness, sickness absence in the past year, expected work ability two years from now, and psychological resources. For each of these dimensions, individual WAI scores were calculated using the standard methodology, and differences between caregivers and non-caregivers were assessed through descriptive statistics, mean-comparison tests, and multivariate regression analysis, controlling for demographic, health, and employment characteristics. The results show that caregivers display slightly less favourable outcomes

1 *Teaching assistant, University of Ljubljana, School of Economics and Business, Kardeljeva ploščad 17, 1000, Ljubljana, Slovenia. Phone: +386 1 589 27 81. E-mail: sara.razman@ef.uni-lj.si.*

2 *Associate professor, University of Ljubljana, School of Economics and Business, Kardeljeva ploščad 17, 1000, Ljubljana, Slovenia. Phone: +386 1 589 24 48. E-mail: petra.d.bonca@ef.uni-lj.si*

3 *Associate professor, University of Ljubljana, School of Economics and Business, Kardeljeva ploščad 17, 1000, Ljubljana, Slovenia. Phone: +386 1 589 26 30. E-mail: mojca.bavdaz@ef.uni-lj.si.*

4 *Associate professor, University of Ljubljana, School of Economics and Business, Kardeljeva ploščad 17, 1000, Ljubljana, Slovenia. Phone: +386 1 589 24 88. E-mail: tjasa.redek@ef.uni-lj.si.*

5 *Associate professor, University of Ljubljana, School of Economics and Business, Kardeljeva ploščad 17, 1000, Ljubljana, Slovenia. Phone: +386 1 589 25 67. E-mail: nina.ponikvar@ef.uni-lj.si.*

in certain health-related WAI dimensions, particularly in diagnosed diseases and expected future work ability, although these associations diminish once demographics, health and employment status are controlled for. These findings suggest that caregiving can indirectly affect work ability through health and well-being pathways, underscoring the importance of supportive labour market and social policies for working caregivers.

***Keywords**: Work ability, Informal caregiving, WAI, Labour market, Slovenia*

***JEL classification**: J14, J21, I10, I12*

1 Introduction

European societies are undergoing profound demographic transformation, with population ageing reshaping labour markets, health systems, and long-term care needs across the continent. Rising life expectancy and changing family structures have intensified the demand for long-term care, making the organisation and sustainability of care provision a central social and economic challenge (OECD, 2023; Eurofound, 2024). A substantial share of this demand is met by informal caregivers, such as family members, relatives, neighbours, or friends who provide assistance without remuneration. Informal care constitutes a crucial yet largely invisible component of welfare systems, contributing vast economic value while simultaneously generating significant burdens for caregivers themselves (Costa-Font and Vilaplana-Prieto, 2025; Hlebec et al., 2024). Current estimates suggest that roughly one in five European adults provides regular unpaid care, with the demand for such care expected to increase dramatically over the coming decades (Baji et al., 2019; Szenkurök et al., 2025).

The provision of informal care has important implications for individuals' health, well-being, and labour-market participation. A broad body of research links caregiving with elevated psychological distress, poorer self-rated physical health, and increased risks of chronic morbidity, although the extent of these effects varies across contexts and caregiving intensity (Longobardo et al., 2023; Roth et al., 2015). These health and psychosocial burdens may in turn influence an individual's capacity to perform paid work, maintain productivity, and remain employed. In this regard, the concept of work ability provides an analytically useful lens for examining how caregiving responsibilities intersect with labour-market functioning. Prior research demonstrates that the WAI predicts sickness absence, disability retirement, and long-term employment outcomes (El Fassi et al., 2013; Magnavita et al., 2024), yet evidence on its relationship with informal caregiving remains limited.

Despite growing recognition that informal caregiving can influence individuals' capacity to work, only a limited number of studies have examined this relationship using validated measures of work ability. Research employing the Work Ability Index (WAI) shows that caregivers may report lower work ability, particularly in dimensions linked to health limitations and psychological fatigue,

with the association being more pronounced among those providing intensive care (Hajek and König, 2016; Airaksinen et al., 2023; Longobardo et al., 2023). At the same time, several studies demonstrate that these differences largely diminish once sociodemographic factors, health status and job characteristics are taken into account, indicating that caregivers' lower work ability may partly reflect compositional factors rather than caregiving itself (Cagney et al., 2021; Mehri et al., 2021). Overall, the existing evidence remains inconclusive and points to a potentially domain-specific relationship between caregiving and work ability that warrants further investigation. The present study addresses this gap by applying the full multidimensional WAI framework, complemented with additional measures of informal caregiving developed by the research team, to examine how caregiving status is associated with variation in work ability among working-age adults in Slovenia.

The Slovenian context provides a compelling case for examining these dynamics. Like many EU member states, Slovenia faces rapid demographic ageing, increasing pressure on long-term care systems, and continued reliance on family-based care (Hlebec et al., 2024; Magnavita et al., 2024). At the same time, Slovenia is still in the process of establishing a fully functioning long-term care system (Kobal Straus & Nagode 2022), which increases the burden shifted onto families and heightens the importance of unpaid caregiving. Maintaining high labour-market participation, particularly among older workers, remains a national priority, while discussions on reconciling paid work and care responsibilities are gaining relevance within broader active-ageing strategies. Understanding whether caregiving is associated with reduced work ability is therefore essential for developing informed employment, health and social policies aimed at sustaining both workforce capacity and caregiver well-being (Hajek & König, 2016).

This paper contributes to the growing body of evidence by analysing the association between informal caregiving and work ability across all seven WAI dimensions using nationally representative data from the Work Ability Survey 2025. The survey incorporates the internationally established WAI, ensuring conceptual comparability with existing occupational health research, while also including additional questions on informal care provision, working conditions, well-being and sociodemographic characteristics specifically relevant to the Slovenian context. The analysis proceeds by first describing the demographic, health and labour-market characteristics of caregivers and non-caregivers. It then examines differences in work ability using descriptive statistics and unconditional regressions, followed by multivariate models that adjust for age, education, physical demands at work and employment status. The results provide new insight into the extent to which informal caregiving is associated with work ability in Slovenia's working-age population and highlight the importance of considering multidimensional measures when assessing the potential labour-market consequences of unpaid care provision.

To clarify the empirical focus of the study, we explicitly formulate the research questions and hypotheses guiding the analysis. This study addresses the following research questions:

> **RQ1**: Do informal caregivers differ from non-caregivers in overall work ability and in specific dimensions of the Work Ability Index?

RQ2: Do any observed differences persist once demographic and job-related characteristics are taken into account?

Based on prior literature and the theoretical mechanisms linking caregiving, health, and labour-market participation, we formulate the following hypotheses:

H1: Informal caregivers exhibit lower overall work ability compared to non-caregivers.

H2: The differences are most pronounced in health-related dimensions of the WAI (diagnosed diseases, work impairment due to illness, sickness absence) and in expected future work ability.

H3: After controlling for age, education, physical job demands and employment status, the association between caregiving and work ability diminishes, indicating that compositional factors explain part of the observed differences.

2 Literature review

Ongoing demographic ageing in Europe has brought informal caregiving to the forefront of debates on the organisation and sustainability of long-term care. As longevity increases and chronic conditions become more prevalent, a substantial share of long-term care needs is met by informal caregivers, such as family members, friends and other unpaid caregivers. Recent estimates indicate that informal caregivers constitute between one fifth and one third of the adult population in many European countries, forming an essential but often invisible pillar of long-term care provision (OECD, 2021; Eurofound, 2024). Consequently, examining the implications of caregiving for caregivers' health, labour market performance, and work ability has become a central theme in health economics, social policy and labour market research (Cattaneo et al., 2025).

2.1 Informal caregiving in ageing societies

Informal caregivers are generally defined as individuals who provide unpaid assistance to someone with functional limitations arising from chronic illness, disability or frailty (Roth et al., 2015; Van den Berg and Spauwen, 2006). Assistance may involve activities of daily living (ADL), such as bathing, dressing, feeding or toileting, as well as instrumental activities of daily living (IADL), including household tasks, transportation, financial management and coordination of medical care (Vitaliano et al., 2003). Unlike formal care, which is provided by trained professionals under an employment contract for remuneration, informal caregiving refers to unpaid assistance that relies on personal ties, emotional bonds, and social expectations of familial responsibility.

The demographic context in Europe is critical for understanding the growing centrality of this unpaid labour. Population ageing has increased the prevalence of multimorbidity, cognitive impairment and functional decline, thereby raising the demand for long-term care (European Commission, 2023).

However, formal long-term care systems remain fragmented, underfunded or institutionally limited in many countries. As a result, informal caregivers absorb a substantial portion of care needs. SHARE data show that 20–30 percent of Europeans aged 50+ provide informal help weekly, and 10–15 percent provide high-intensity care (SHARE-ERIC, 2024). The prevalence of informal care is particularly pronounced among women, individuals aged 40–64, and those living with elderly parents (Dung Le and Ibuka, 2023; Krämer and Bleidorn, 2025; Mehri et al., 2021). Although unpaid, informal care generates substantial economic value. Several recent studies have attempted to quantify its societal cost by imputing the opportunity cost of labour supply, lost productivity, and replacement cost equivalent to formal care provision. Ekman et al. (2021) estimate that informal care in Sweden corresponds to roughly 3 percent of GDP, with more than half of the cost attributable to caregivers' foregone earnings. Similar magnitudes are reported for continental European countries, where informal caregivers frequently reduce working hours, reject promotions, or exit the labour force (OECD, 2021).

The distribution of caregiving is shaped by gender norms, labour market institutions and welfare state arrangements. Women continue to shoulder the majority of caregiving responsibilities, often resulting in cumulative disadvantages through lower earnings, pension gaps and reduced career progression (Eurofound, 2024). Cross-national evidence shows that while participation in informal caregiving is common across all age groups, its intensity peaks in midlife, where work and care responsibilities intersect most strongly (Quashie et al., 2022). Caregiving prevalence is typically lower among younger adult cohorts but increases sharply from age 40 onwards, reflecting the growing health needs of parents and relatives.

Beyond institutional arrangements, caregiving patterns are also shaped by cultural expectations and social norms regarding family responsibility. Recent European evidence indicates that informal family caregiving remains a central pillar of long-term care provision across diverse national contexts and is projected to increase substantially in the coming decades, particularly where formal care capacity is limited (Cattaneo et al., 2025). Empirical estimates show that informal caregivers account for a large share of total long-term care provision in the EU, reflecting continued reliance on family-based support across welfare states (Abed et al., 2025). These findings suggest that caregiving behaviour is influenced by a combination of institutional structures and normative expectations concerning familial duty.

Furthermore, caregiving responsibilities are increasingly combined with paid work. Verbakel et al. (2017) report that in most EU countries, the majority of working-age caregivers remain employed, although often in part-time roles or under conditions of reduced working capacity. This intersection of work and care obligations is the central mechanism through which caregiving may affect labour market outcomes and thus features prominently in the conceptualisation of work ability.

Socioeconomic resources and geographic context also influence caregiving arrangements across Europe. Recent European evidence shows that individuals with greater socioeconomic resources are more likely to use formal care options, while lower-income individuals often depend more on unpaid

family care due to limited resources and affordability constraints (Quashie et al., 2022). Analyses of long-term care systems further highlight how inequalities in the availability and access to formal services contribute to divergent care patterns both across and within countries. Geographic disparities in service provision, for example, between urban and rural areas, can exacerbate these differences, as rural regions often have fewer formal service options, increasing reliance on informal care networks. These structural patterns suggest that caregiving behaviour reflects not only individual caregiver characteristics but also broader socioeconomic and regional contexts (Boswell et al., 2025).

2.2 The impact of informal caregiving

A substantial body of literature has examined the health consequences of caregiving, yielding mixed but theoretically coherent findings. Two competing frameworks dominate the discussion: stress theory (Cejalvo et al., 2025; Wang et al., 2023) and the healthy caregiver hypothesis (Fredman et al., 2010; Roth et al., 2015). According to stress theory, the sustained, unpredictable and emotionally demanding nature of caregiving creates chronic stress exposure that can impair immune functioning, accelerate physiological damage and contribute to both mental and physical morbidity (Vitaliano et al., 2003). Numerous empirical studies document elevated risks of depression, anxiety, hypertension, musculoskeletal disorders, sleep disturbances, and reduced self-rated health among caregivers (Janson et al., 2022). In contrast, the healthy caregiver hypothesis posits that caregivers may exhibit lower mortality and equal or better health outcomes than non-caregivers due to selection (healthier individuals are more likely to assume and maintain caregiving roles) and potential psychosocial benefits from caregiving, such as increased physical activity, purpose, and emotional reward (Fredman et al., 2010; Roth et al., 2015). Recent evidence suggests that both mechanisms operate simultaneously: caregiving is associated with modest reductions in mortality overall, but also with increased risks of chronic stress-related morbidity (Cattaneo et al., 2025; Mehri et al., 2021). The divergence likely reflects heterogeneity in caregiving intensity, duration, types of tasks, and the availability of formal support.

The occupational and labour market consequences of caregiving are similarly complex. Caregiving can reduce labour supply through exit from employment, changes in contract type, or reductions in working hours, but the magnitude varies widely across institutional settings (Ciani, 2012; Bauer & Sousa-Poza, 2015). Moreover, even when caregivers remain employed, caregiving responsibilities may affect productivity and subjective work performance through fatigue, time constraints, and reduced psychological resources. These factors provide a strong theoretical rationale for examining work ability, which integrates health, functional capacity, job demands, and expectations about future work participation.

2.3 Informal caregiving and work ability

Work ability refers to an individual's capacity to perform their job, given the interaction between health status, functional resources, job demands and psychosocial factors (Ilmarinen, 2009). Empirical research consistently demonstrates that work ability declines with age (Ilmarinen, 2009; von Bonsdorff et al., 2020), is lower among individuals in physically demanding jobs (Airaksinen et al., 2023), and strongly predicts sickness absence, disability retirement and productivity loss (Bethge & Radoschewski, 2010). Higher education is positively associated with better work ability, reflecting differential job demands and health behaviours (Airaksinen et al., 2023).

Despite the widespread use of WAI in occupational health research, relatively few studies have examined the relationship between informal caregiving and work ability in a systematic manner (Hajek & König, 2016; Airaksinen et al., 2023). Existing evidence suggests that caregiving may affect specific components of work ability, such as psychological resources, health-related constraints, and expectations of future work ability, more strongly than the composite index (Hajek & König, 2016). However, empirical findings remain inconsistent and are often based on small or non-representative samples, or they lack extensive adjustment for socio-demographic and job-related factors (Cagney et al., 2021). Overall, the literature directly linking informal caregiving to WAI outcomes remains scarce, despite the growing policy relevance of understanding how unpaid caregiving intersects with labour market participation in ageing societies.

The intersection between caregiving and work ability has attracted growing attention among researchers in occupational health and labour economics (Hajek & König, 2016; Airaksinen et al., 2023). Conceptually, several mechanisms explain how caregiving may shape work ability. First, caregiving can generate emotional strain, physical effort and sleep disruption, increasing the risk of chronic stress–related morbidity, as suggested by stress theory (Vitaliano et al., 2003. European cohort studies document elevated rates of musculoskeletal disorders, fatigue and depression among caregivers (Janson et al., 2022), which are reflected in the WAI dimensions capturing diagnosed diseases, illness-related work impairment and sickness absence (WAI3–WAI5). Second, caregiving may influence psychological resilience and cognitive functioning (WAI7); while the burden of care can reduce coping resources, the healthy caregiver hypothesis highlights potential psychosocial benefits such as identity reinforcement and behavioural activation (Fredman et al., 2010; Roth et al., 2015; Mehri et al., 2021). Third, time pressure and job–care conflicts may reduce caregivers' perceived ability to meet job demands (WAI2) and lower expectations regarding their future work capacity (WAI6), particularly under high-intensity care (Airaksinen et al., 2023; Ciani, 2012). Finally, labour-market sorting may lead caregivers to concentrate in part-time, lower-quality, or physically demanding jobs, influencing baseline differences in ergonomic exposure and job stressors visible in WAI1 and WAI2 (Bauer & Sousa-Poza, 2015). These combined pathways demonstrate that caregiving may affect specific components of work ability through distinct health, psychosocial and labour-market mechanisms and reinforce the need for analyses that account for demographic, socioeconomic and job-related characteristics.

Only a limited number of empirical studies have examined work ability directly as an outcome. Hajek and König (2016), using German survey data, find that high-intensity caregivers exhibit lower WAI scores, largely explained by psychological fatigue and musculoskeletal complaints. Airaksinen et al. (2023) show that work–life conflict functions as a mediator linking caregiving to diminished work ability, suggesting that the strain arises not only from care tasks themselves but also from the broader incompatibility between caregiving and employment. Conversely, other studies indicate that once socioeconomic status, health, and job characteristics are controlled for, differences in work ability between caregivers and non-caregivers become substantially smaller or statistically non-significant (Cagney et al., 2021; Cattaneo, 2025). This pattern suggests that observed disparities may be driven less by caregiving per se and more by the structural environment in which caregivers are embedded. The emerging literature therefore highlights the importance of analysing work ability not solely as a health or productivity measure, but as a multifaceted construct shaped by both individual vulnerabilities and broader labour market and social conditions.

3 Methodology

This study draws on data from the Work Ability Survey 2025, a cross-sectional survey conducted in Slovenia in February 2025 among adults aged 30 to 65 years who were actively participating in the labour market. The lower age bound of 30 years was chosen to exclude the youngest segment of the labour force, which typically exhibits the highest levels of work ability and comparatively low caregiving prevalence. The upper age bound of 65 years was chosen to exclude the retired population, in order to ensure that the sample consists of individuals who are economically active, in line with the definition of the labour force used by the International Labour Organization. Individuals not participating in the labour market were excluded, as the study focuses on the interaction between caregiving and work ability among the working-age population.

To ensure the reliability and validity of the measurement instruments, as well as to support comparability with existing European evidence, the questionnaire integrates established, validated scales, most prominently the Work Ability Index (Ilmarinen et al., 2005), alongside selected items from the CINDI Health Monitor Survey (WHO Regional Office for Europe, 2001) and the European Health Interview Survey (Eurostat, 2018). The inclusion of these standardised instruments ensures conceptual consistency with international occupational health and population-health frameworks and aligns with methodological practices employed by the Statistical Office of the Republic of Slovenia.

The questionnaire was designed by a four-member interdisciplinary research team with expertise in health economics, labour economics, microeconomics, and questionnaire methodology. Prior to fielding, the instrument underwent expert review and technical validation by Valicon, leveraging their extensive experience in web-based survey design, which ensured clarity, reliability and respondent accessibility. The survey collected comprehensive information on respondents' employment status and working

conditions, self-reported work ability across all seven WAI dimensions, diagnosed physical and mental health conditions, sickness absence, well-being, lifestyle factors, informal care provision, and core sociodemographic characteristics including gender, age, education and region of residence. Data collection was carried out through a computer-assisted web interview (CAWI) administered by Valicon, a recognised commercial research agency operating a long-established online respondent panel.

Informal caregiving was measured using a survey question that asked respondents whether they regularly provide unpaid care or assistance to a person with health-related functional limitations. Respondents answering affirmatively were classified as informal caregivers. The wording of the question explicitly referred to regular provision of care, thereby excluding occasional or sporadic assistance. The questionnaire further captured information on the type of support provided, including assistance with activities of daily living (ADL), such as personal care tasks, and instrumental activities of daily living (IADL), such as household tasks or coordination of services. In the empirical analysis, caregiving status is operationalised as a binary indicator distinguishing caregivers from non-caregivers.

In the empirical analysis, caregiving status is operationalised as a binary indicator distinguishing caregivers from non-caregivers. This specification captures the presence of regular unpaid care responsibilities while maintaining statistical power and comparability across the seven WAI dimensions. Alternative specifications using more detailed caregiving categories were estimated as robustness checks and yielded substantively similar results; therefore, the binary specification is retained in the main models.

3.1 Data and sample characteristics

The final analytical sample consists of 1,075 respondents aged 30–65 years who were economically active at the time of the survey. Women constitute 50.8 percent of the sample, and the age distribution mirrors that of the national working-age population: approximately one quarter are aged 30–39, one third 40–49, another third 50–59, and roughly 8.5 percent are 60 or above. Regional representation corresponds closely to national demographic patterns.

Fewer than 15 percent have primary education, around one third hold upper secondary education, and nearly one half have post-secondary or tertiary education. Labour market characteristics reflect a predominantly standard-employment environment: 80 percent report being regularly employed, 4.6 percent employed in micro firms or by entrepreneurs, 4.2 percent self-employed, and 7.3 percent unemployed. Respondents evaluated their general health positively: 24 percent reported “very good”, 51 percent “good”, and fewer than 8 percent reported “poor” or “very poor” health.

3.2 Analytical approach and empirical model

The objective of the empirical analysis is to examine the association between informal caregiving and work ability. In the literature, work ability is operationalised in several ways, most commonly through indicators such as self-rated functional capacity, work limitations due to health, or proxies linked to labour market outcomes such as productivity, sickness absence, or disability retirement (Ilmarinen, 2009; von Bonsdorff et al., 2020). Among the available measurement approaches, the Work Ability Index, developed by the Finnish Institute of Occupational Health (Ilmarinen et al., 2005), has become the most widely used and internationally validated tool in occupational health and active ageing research. The WAI conceptualises work ability as a multidimensional construct comprising seven interrelated dimensions. Dimensions 1 and 2 capture current perceived work capacity; dimensions 3 to 5 reflect health status and functional limitations through diagnosed diseases, illness-related work impairment and sickness absence; dimension 6 assesses expected future work ability; and dimension 7 measures psychological and motivational resources. Together, these dimensions form a composite score that has demonstrated strong predictive validity for key labour market outcomes, including sickness absence, early labour market exit and disability retirement (Bethge & Radoschewski, 2010; El Fassi et al., 2013). In this study, all seven WAI dimensions were scored according to the official methodology and analysed individually and as a composite indicator.

Given the multidimensional nature of work ability and the demographic heterogeneity of care-givers, the empirical analysis proceeds through two complementary regression specifications. First, simple ordinary least squares (OLS) models are estimated in which the dependent variable is either the composite WAI score or one of its seven dimensions (WAId_dd), and caregiving status is the sole explanatory variable. These baseline models allow us to examine whether caregivers differ from non-caregivers in work ability when considered in isolation. Second, multivariate OLS regressions of the form

$$WAI_i = \alpha + \beta_1\, caregiver + X'_i + \varepsilon_i \qquad (1)$$

are estimated to assess whether caregiving remains associated with work ability after adjusting for observable characteristics. The control vector includes age (measured as a continuous midpoint of five-year bands), education (three categories: primary or less, upper secondary, tertiary), physical work (a five-point scale capturing physical strain), and employment status (distinguishing standard from non-standard employment). These covariates account for well-documented differences in health, human capital and job characteristics between caregivers and non-caregivers. Comparing baseline and controlled estimates therefore enables us to determine whether caregiving itself is associated with work ability or whether any observed differences are driven by compositional factors. Educational attainment is included not only as an indicator of human capital and job characteristics, but also as a proxy for socioeconomic position. Socioeconomic resources, including income,

may influence caregiving arrangements in two ways: on the demand side, households with greater financial resources are more likely to access formal care services; on the supply side, individuals with higher earnings face greater opportunity costs when allocating time to unpaid caregiving. Although the survey does not include a direct measure of household income or regional service availability, education captures part of this socioeconomic gradient.

All regression models were estimated using ordinary least squares. Although the composite Work Ability Index and its subdimensions are bounded scales, they consist of multi-item summary measures with relatively wide ranges and are commonly treated as approximately continuous in occupational health research. In the present sample, the distribution of WAI scores does not exhibit substantial clustering at the boundaries, supporting the use of linear modelling. OLS enables straightforward interpretation of coefficients in terms of point differences in work ability and facilitates comparison across specifications and dimensions. To account for potential heteroscedasticity, all models were estimated using heteroskedasticity-robust (Huber–White) standard errors, ensuring consistent statistical inference even if the error variance is not constant across observations. The use of linear regression models for the composite WAI and its subdimensions aligns with established empirical practice in occupational health and caregiving research, where the WAI is routinely analysed as a continuous outcome within OLS frameworks (e.g., Bethge & Radoschewski, 2010; El Fassi et al., 2013; Hajek & König, 2016; Airaksinen et al., 2023). Recent studies examining work ability in relation to employment conditions, psychosocial factors, and caregiving responsibilities also treat WAI scores as approximately continuous and estimate linear regression models (Magnavita et al., 2024; Cattaneo et al., 2024). Adhering to this methodological tradition enhances comparability with existing European evidence and facilitates transparent interpretation of coefficient magnitudes as point differences in work ability.

First, a correlation matrix was estimated for all WAI dimensions and for the key explanatory variables. The matrix serves two methodological purposes: it provides a validity check of the WAI construct by confirming expected patterns of association among the dimensions, and it reveals the strength and direction of correlations between status of informal-caregiver, demographic characteristics, health status, employment status and work ability.

3.3 Descriptive statistics

Table 1 presents descriptive information for all seven dimensions of WAI. Each dimension is coded such that higher values indicate better work ability, fewer health-related constraints or stronger psychological resources. The table also provides the mean value for each component in the analytical sample.

Table 1: Work Ability Index dimensions and mean values

Dimension	Description	Scale	Mean
WAI1	Current work ability compared to lifetime best	0–10	7.74
WAI2	Work ability relative to physical and mental job demands	2–10	8.34
WAI3	Diagnosed diseases (re-scaled; higher = better health)	1–7	5.01
WAI4	Work impairment due to illness	1–6	5.11
WAI5	Sickness absence in the last 12 months	1–5	4.23
WAI6	Expected work ability in two years	1–7	6.10
WAI7	Psychological resources (e.g., resilience, motivation)	0–4	2.68

Source: Authors based on the WAI Survey 2025.

The descriptive values indicate that respondents in the sample generally report high levels of current work ability. WAI1 averages 7.74 on a 0–10 scale, suggesting that most individuals perceive themselves as performing close to their lifetime best. Perceived ability relative to physical and mental job demands (WAI2) is similarly strong at 8.34, consistent with a relatively healthy and labour-active population. The health-related dimensions—WAI3, WAI4 and WAI5—fall into the mid-range of their scales, indicating variation in diagnosed diseases, illness-related work impairment and sickness absence. Expected future work ability (WAI6) also lies in the upper part of the distribution, implying moderate optimism among workers regarding their capacity two years ahead. Psychological resources (WAI7), which range from 0 to 4, average 2.68, suggesting generally adequate motivational and coping reserves.

Importantly, 24.37 percent of respondents reported regular provision of unpaid care, a proportion consistent with recent European evidence on unpaid caregiving among working-age adults. Because caregivers differ systematically from non-caregivers in characteristics such as age, education, health status and job type, descriptive statistics alone cannot reveal whether caregiving is independently associated with work ability. Thus, the regression analysis presented in the following section examines whether the modest differences observed in some WAI dimensions persist once these structural factors are taken into account.

4 Results and discussion

To provide an initial overview of the relationships among work ability indicators and key covariates, Table 2 reports pairwise correlations between the composite WAI score, its seven dimensions, and the main explanatory variables used in subsequent models. The correlation matrix serves as a diagnostic tool, confirming expected associations between WAI components and illustrating how demographic, health and job-related characteristics relate to work ability prior to multivariate adjustment.

Table 2: Pairwise correlations between WAI, WAI dimensions and covariates

	WAI	WAI1	WAI2	WAI3	WAI4	WAI5	WAI6	WAI7	Caregiver	Activity	Education	Employment status	Age_mid
WAI	1.00												
WAI1	0.80	1.00											
WAI2	0.73	0.65	1.00										
WAI3	0.65	0.37	0.27	1.00									
WAI4	0.77	0.56	0.50	0.45	1.00								
WAI5	0.62	0.39	0.29	0.38	0.45	1.00							
WAI6	0.66	0.41	0.41	0.23	0.43	0.31	1.00						
WAI7	0.56	0.42	0.45	0.23	0.39	0.23	0.31	1.00					
Care-giver	-0.05	-0.00	-0.04	-0.05	-0.06	-0.00	-0.06	-0.02	1.00				
Activity	-0.15	-0.08	-0.17	-0.01	-0.13	-0.13	-0.13	-0.03	0.09	1.00			
Educa-tion	0.18	0.21	0.20	0.04	0.12	0.15	0.16	0.08	-0.06	-0.34	1.00		
Emp. status	-0.01	-0.24	-0.03	-0.07	-0.08	0.07	0.00	-0.08	0.02	0.05	-0.10	1.00	
Age_ mid	-0.24	-0.26	-0.18	-0.22	-0.14	-0.08	-0.17	-0.06	0.08	0.05	-0.13	0.08	1.00

Source: Authors based on the WAI Survey 2025.

The composite WAI score is strongly and positively correlated with all seven of its constituent dimensions, with coefficients ranging from 0.56 to 0.80, confirming that the dimensions capture related yet distinct facets of work ability. Age displays consistently negative correlations with the total WAI and with each individual dimension, mirroring the regression results that indicate a systematic decline in work ability as workers grow older. Education, by contrast, is positively associated with the overall WAI and with most of its components, while physical work activity shows a negative association with work ability, suggesting that physically demanding jobs correspond to lower perceived work capacity and greater work-related strain. Notably, the correlations between caregiving status and any of the WAI indicators are very small in magnitude, generally around −0.05 and never exceeding −0.06. This near-zero relationship is fully consistent with the multivariate estimates, where caregiving status does not emerge as a statistically significant determinant of work ability once demographic and job-related characteristics are taken into account.

To explore whether informal caregivers differ systematically from non-caregivers in any of the WAI dimensions, we first estimated our model, using the basic specification with only informal caregiver status as a regressor for each of the WAI components as the dependent variable. The coefficient on the caregiver dummy captures the unconditional mean difference between caregivers and non-caregivers.

Table 3: Regressions results of WAI and WAI dimensions model – basic specification

Variable	WAI (total)	WAI1	WAI2	WAI3	WAI4	WAI5	WAI6	WAI7
Caregiver	-0.884	-0.021	-0.112	-0.259*	-0.186*	-0.009	-0.235*	-0.030
	(0.546)	(0.148)	(0.107)	(0.150)	(0.096)	(0.090)	(0.139)	(0.058)
Constant	39.49***	7.75***	8.38***	5.01***	5.11***	4.23***	6.10***	2.68***
	(0.258)	(0.071)	(0.049)	(0.070)	(0.044)	(0.044)	(0.063)	(0.030)
N	996	1,075	996	1,075	996	996	996	1,075
R^2	0.0028	0.0000	0.0012	0.0030	0.0042	0.0000	0.0032	0.0002

Standard errors in parentheses. Robust (Huber–White) standard errors reported.
*** p < 0.01, ** p < 0.05, * p < 0.10.
Source: Authors based on the WAI Survey 2025.

The results in Table 3 reveal three patterns. First, the coefficient for caregiver in the regression using the composite WAI score is negative (–0.884), but no longer statistically significant at conventional levels once robust standard errors are applied (p = 0.106). This indicates that caregivers, on average, report slightly lower overall work ability than non-caregivers. However, the effect is small in magnitude relative to the overall mean and accounts for less than one percent of the variance ($R^2 \approx 0.003$). Second, when examining individual WAI dimensions, most caregiver coefficients are negative yet statistically insignificant. The most notable, though still modest, patterns appear in WAI3 (diagnosed diseases), where caregivers show somewhat lower scores (–0.259, p = 0.073), and in WAI4 (work impairment due to illness), for which the association is statistically significant (–0.186, p = 0.042), suggesting slightly greater illness-related limitations at work. A similar tendency is visible for WAI6, capturing expected future work ability (–0.235, p = 0.072), implying that caregivers are marginally less optimistic about their future capacity to work. Third, for WAI7, reflecting psychological resources, the caregiver coefficient is small and statistically insignificant, indicating no clear unconditional differences in psychological resilience between caregivers and non-caregivers. Overall, the bivariate findings suggest slightly lower work ability among caregivers, particularly in the health and impairment related dimensions, but caregiving status alone contributes very little to explaining the variation. This highlights the need to incorporate further factors such as age, education and employment conditions.

To control for key confounding factors, we next extended our model specification by including the set of control variables: physical work, educational attainment, employment status and age. All models were estimated using ordinary least squares regression with heteroscedasticity-robust standard errors, to ensure valid statistical inference in the presence of potential heteroscedasticity.

The multivariate estimates in Table 4 show that once individual and job-related characteristics are taken into account, caregiving status no longer retains statistical significance. Although the coefficients for caregivers remain predominantly negative for the composite WAI measure and for several dimensions (WAI2, WAI3, WAI4 and WAI6), their confidence intervals clearly include zero, indicating that the modest raw differences identified in the bivariate models largely reflect compositional factors rather than an independent effect of informal caregiving. In this sample, caregiving itself is therefore not associated with systematically lower work ability once observable covariates are controlled for.

Table 4: Regressions results of WAI and WAI dimensions model – specification with control variables

Variable	WAI (total)	WAI1	WAI2	WAI3	WAI4	WAI5	WAI6	WAI7
Caregiver	-0.377 (0.527)	0.095 (0.139)	-0.021 (0.104)	-0.166 (0.147)	-0.121 (0.094)	0.028 (0.089)	-0.143 (0.141)	-0.014 (0.058)
Employment status (2)	-0.044 (0.782)	0.084 (0.194)	-0.093 (0.153)	-0.178 (0.239)	-0.334** (0.164)	0.332** (0.128)	0.068 (0.193)	0.073 (0.094)
Employment status (3)	—	-1.780*** (0.268)	—	-0.236 (0.252)	—	—	—	-0.262*** (0.094)
Gender (Woman)	-2.463*** (0.434)	-0.408*** (0.115)	-0.290*** (0.084)	-0.586*** (0.121)	-0.497*** (0.076)	-0.289*** (0.075)	-0.275** (0.110)	-0.168*** (0.051)
Physical activity (activity)	-1.314*** (0.471)	-0.037 (0.125)	-0.304*** (0.093)	0.037 (0.130)	-0.252*** (0.083)	-0.230*** (0.083)	-0.303** (0.122)	-0.003 (0.055)
Education	1.853*** (0.431)	0.617*** (0.116)	0.382*** (0.088)	0.075 (0.122)	0.181** (0.077)	0.281*** (0.077)	0.398*** (0.113)	0.102** (0.051)
Age (age_ mid)	-0.145*** (0.019)	-0.041*** (0.005)	-0.020*** (0.004)	-0.039*** (0.005)	-0.014*** (0.003)	-0.007** (0.003)	-0.024*** (0.005)	-0.003 (0.002)
Constant	43.530*** (1.622)	8.545*** (0.461)	8.632*** (0.337)	7.021*** (0.422)	5.722*** (0.285)	4.076*** (0.294)	6.488*** (0.428)	2.692*** (0.187)
N	995	1,074	995	1,074	995	995	995	1,074
R^2	0.120	0.169	0.087	0.074	0.087	0.055	0.063	0.029

Standard errors in parentheses. Robust (Huber–White) standard errors reported.
*** p < 0.01, ** p < 0.05, * p < 0.10.
Source: Authors based on the WAI Survey 2025.

Age, education and the physical demands of work emerge as the key correlates of work ability across specifications. Age exhibits a consistently negative and statistically significant association with both the total WAI score and with dimensions WAI1 through WAI6. Each additional year of age is linked to a gradual decline in current work ability, perceived fit to job demands,

and expectations about future work ability, as well as to increased health-related constraints, mirroring well-established age gradients documented in occupational health research. By contrast, educational attainment exerts a positive and significant influence on the overall WAI and on multiple subdimensions (WAI1, WAI2, WAI5, WAI6 and WAI7), suggesting that more highly educated workers benefit from better working conditions, enhanced health literacy, and stronger psychosocial resources. Physical activity at work displays a negative relationship with the composite index and with several dimensions, most notably WAI2, WAI4, WAI5 and WAI6. This pattern indicates that employees exposed to more physically demanding tasks experience lower perceived ability relative to job requirements, greater work impairment and increased sickness absence, consistent with the cumulative strain associated with manual work.

Employment status shows a more differentiated association. Relative to standard employment arrangements, certain non-standard forms of employment, particularly employment category (3), are associated with significantly lower current work ability (WAI1) and weaker psychological resources (WAI7). Employment status (2), by contrast, does not differ significantly in most dimensions, but is associated with fewer reported sickness absence days (WAI5). This differentiated pattern indicates that employment heterogeneity matters and that not all non-standard arrangements are equally linked to work ability outcomes. Overall, the multivariate evidence demonstrates that structural and sociodemographic factors constitute far more powerful predictors of work ability than caregiving status. The initial negative association between caregiving and work ability observed in the bivariate analysis thus appears to be primarily driven by differences in workforce composition rather than by caregiving itself.

Work ability levels are generally high, yet they display a clear age gradient and are systematically lower among individuals employed in physically demanding occupations or less favourable employment arrangements. In the simple models, informal caregivers appear to have modestly lower scores on certain WAI dimensions, particularly those related to health constraints and expectations of future work ability. However, once age, education, physical workload and employment status are taken into account, caregiving status itself no longer emerges as a statistically significant determinant of either the composite WAI score or any of its individual components. This indicates that the observed raw differences between caregivers and non-caregivers are largely compositional, since caregivers tend on average to be older and more frequently engaged in physically strenuous or insecure forms of work.

To assess whether the association between informal caregiving and work ability varies across population subgroups, we extended the specification in Table 4 by introducing interaction terms between caregiving status and gender or employment status. All models were estimated using ordinary least squares with robust standard errors. The interaction models were estimated for the composite WAI score and for each of the seven WAI dimensions. Table 5 presents the estimated interaction coefficients.

Table 5: Interaction effects between caregiving and gender/employment status

Variable	WAI (total)	WAI1	WAI2	WAI3	WAI4	WAI5	WAI6	WAI7
Caregiver	-1.745** (0.724)	-0.184 (0.206)	-0.279* (0.152)	-0.369* (0.205)	-0.239* (0.126)	-0.138 (0.129)	-0.446** (0.206)	-0.015 (0.087)
Gender	-3.125*** (0.486)	-0.511*** (0.130)	-0.403*** (0.094)	-0.665*** (0.137)	-0.562*** (0.084)	-0.379*** (0.086)	-0.440*** (0.120)	-0.181*** (0.060)
Caregiver × Gender	2.736*** (1.048)	0.429 (0.277)	0.468** (0.206)	0.326 (0.295)	0.266 (0.187)	0.372** (0.180)	0.679** (0.277)	0.055 (0.118)
Employment status (2)	-0.120 (0.902)	-0.050 (0.228)	-0.182 (0.169)	-0.264 (0.285)	-0.293 (0.194)	0.385*** (0.144)	0.166 (0.197)	0.133 (0.110)
Employment status (3)	—	-1.857*** (0.302)	—	-0.279 (0.286)	—	—	—	-0.232** (0.109)
Caregiver × Employment (2)	0.298 (1.766)	0.456 (0.421)	0.302 (0.358)	0.295 (0.522)	-0.134 (0.356)	-0.169 (0.303)	-0.313 (0.490)	-0.198 (0.210)
Caregiver × Employment (3)	—	0.297 (0.645)	—	0.162 (0.599)	—	—	—	-0.130 (0.215)
N	995	1,074	995	1,074	995	995	995	1,074
R^2	0.127	0.173	0.093	0.075	0.090	0.059	0.070	0.030

Standard errors in parentheses. Robust (Huber–White) standard errors reported.
*** p < 0.01, ** p < 0.05, * p < 0.10.
Source: Authors based on the WAI Survey 2025.

The interaction analysis provides limited evidence of systematic heterogeneity in the relationship between caregiving and work ability. In most specifications, the interaction terms between caregiving and employment status are small and statistically insignificant, suggesting that the association between caregiving and work ability does not differ meaningfully across employment categories. The interaction between caregiving and gender reveals more nuanced patterns. For the composite WAI score and for selected dimensions (notably WAI2 and WAI6), the interaction term is positive and statistically significant, indicating that the negative association between caregiving and work ability observed among men is substantially weaker than among women. However, these effects are not consistent across all dimensions and remain modest in magnitude. Overall, the findings do not point to strong or systematic distributional differences in the impact of caregiving by gender or employment status.

5 Conclusions

The findings of this study show that informal caregiving, while widespread and socially indispensable, is not in itself a major determinant of work ability among the Slovenian working-age population. Caregivers exhibit slightly lower scores in several health-related dimensions of the WAI, particularly in diagnosed diseases, work impairment and expectations regarding future work ability, but these disparities largely disappear once differences in age, education, physical work demands and employment conditions are taken into account. Caregivers tend to be older and more frequently engaged in physically demanding or less secure forms of employment, and it is these structural factors, rather than caregiving status alone, that most strongly shape work ability outcomes. More broadly, the results show that age, educational attainment and ergonomic workload remain the dominant correlates of work ability, consistent with international evidence on occupational health and ageing.

Placing these findings in a broader European perspective, the Slovenian results are broadly consistent with existing cross-national evidence. Studies from Germany and Nordic countries similarly report modest or statistically weak associations between caregiving and work ability when socioeconomic and job-related factors are controlled for (Hajek & König, 2016; Airaksinen et al., 2023). Moreover, comparative analyses show that differences in work capacity among caregivers often reflect compositional characteristics, such as age and employment conditions (Cagney et al., 2021; Quashie et al., 2022). In the context of long-term care systems, Slovenia shares features with other European countries that rely substantially on informal family support (Nagode & Lebar, 2019), suggesting that the absence of strong independent caregiving effects on work ability may not be unique to the Slovenian case. Rather, the results align with emerging European evidence indicating that structural labour-market factors are more decisive predictors of work ability than caregiving status alone.

The modest negative associations observed in the bivariate models, particularly for health-related dimensions and expected future work ability, are consistent with studies highlighting stress-related morbidity and fatigue among caregivers (Vitaliano et al., 2005; Cejalvo et al., 2025). However, the disappearance of these effects after adjustment aligns with research showing that caregiving differences are largely explained by age and socioeconomic position (Cagney et al., 2021; Quashie et al., 2022). The strong age gradient identified in our models further confirms well-established findings in occupational health research that work ability declines systematically over the life course (von Bonsdorff et al., 2020).

From a policy perspective, these findings indicate that efforts to support work ability among caregivers should extend beyond caregiving status itself and address the broader structural conditions in which work and care responsibilities intersect. In contexts such as Slovenia, where a formal long-term care system is still being established, the absence of comprehensive institutional support places a disproportionate burden on families, making workplace conditions and labour-market policies particularly consequential.

Measures that reduce physical strain at work, improve access to stable and higher-quality employment, and promote opportunities for skill upgrading are likely to enhance work ability for both caregivers and non-caregivers. At the same time, the slightly lower expectations of future work ability observed among caregivers underscore the importance of policy instruments that alleviate role strain, such as flexible working arrangements, paid caregiver leave, respite services, and employer-based accommodations explicitly designed to support employees with care obligations. Evidence from countries with more developed long-term care systems shows that such measures can mitigate the negative spillovers of caregiving on employment trajectories and help prevent premature labour-market exit. Strengthening the compatibility of work and care roles is therefore essential not only for maintaining workforce capacity but also for ensuring that the implementation of new long-term care systems does not inadvertently exacerbate inequalities in health, productivity and economic security.

Future research should continue to investigate the dynamic interplay between caregiving and work ability, particularly through longitudinal approaches that capture changes over time and distinguish between short-term strain and long-term adaptation. Greater attention to caregiving intensity, duration and type of care tasks would also enrich the understanding of which groups of caregivers face elevated risks and under what labour-market conditions. As population ageing accelerates, clarifying these mechanisms will be increasingly important for designing sustainable employment, health and social policies that support both productive longevity and the well-being of those who provide essential unpaid care.

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Age Diversity Within Occupational Groups and Labour Productivity: Evidence from Matched Employee–Employer Slovenian Data

Original scientific paper

Nina Ponikvar[1], Katja Zajc Kejžar[2], Darja Peljhan[3], Aleša Saša Sitar[4]

ABSTRACT

This paper examines how workforce age diversity affects firm performance and whether this impact varies across occupation and sector. Age diversity is measured with two dimensions: age separation (standard deviation and coefficient of variation of employee age) and age variety (Blau index). We apply a matched employer–employee data for Slovenian firms with more than fifty employees from 2006 to 2016. Fixed-effects panel regressions show that firms with older workforces have lower labour productivity on average, while greater age diversity enhances it. Both age separation and age variety have positive and significant effects, indicating that complementarities between younger and older workers—through knowledge transfer and experience sharing—outweigh potential coordination costs. However, the effects vary by occupation and sector. Age diversity most strongly improves productivity among experts and blue-collar workers in low- and medium-technology manufacturing, while the effects are weaker for managers and insignificant in services and high-technology sectors. These results suggest that the benefits of age diversity depend on task structure, skill requirements, and collaboration intensity. This study contributes to the literature by providing large-scale evidence from a small open economy and by distinguishing between multiple aspects of age diversity. Policy implications highlight the importance of age-inclusive human resource practices that foster intergenerational collaboration, support lifelong learning, and adapt workplaces to diverse age structures—key factors for sustaining productivity in ageing societies.

1 *Associate Professor, University of Ljubljana, School of Economics and Business, Kardeljeva pl. 17, 1000 Ljubljana, Slovenia, E-mail: nina.ponikvar@ef.uni-lj.si*

2 *Full Professor, University of Ljubljana, School of Economics and Business, Kardeljeva pl. 17, 1000 Ljubljana, Slovenia, E-mail: katja.zajc@ef.uni-lj.si*

3 *Full Professor, University of Ljubljana, School of Economics and Business, Kardeljeva pl. 17, 1000 Ljubljana, Slovenia, E-mail: darja.peljhan@ef.uni-lj.si*

4 *Assistant Professor, University of Ljubljana, School of Economics and Business, Kardeljeva pl. 17, 1000 Ljubljana, Slovenia, E-mail: alesa-sasa.sitar@ef.uni-lj.si*

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***JEL classification**: C23, J21, J24, L25*

1 Introduction

The progressive ageing of population poses one of the most significant socioeconomic challenges for Europe this century. As people live and work longer, the proportion of older workers rises, age diversity is becoming an increasingly important issue for organisations to manage effectively (OECD, 2020). In this demographic context, understanding how age diversity within organisations influences firm performance has become crucial for ensuring sustainable productivity growth and competitiveness. Firms are the key transmission channel through which demographic changes affect aggregate economic performance, making this topic particularly relevant for both academic inquiry and policy design (Börsch-Supan, 2021).

Age-diverse workforces combine the experience and tacit knowledge of older employees with the innovative capacity and technological adaptability of younger workers. Drawing on information/decision-making theory (Van Knippenberg et al., 2004), age diversity can enhance creativity, learning, and problem-solving through a wider pool of perspectives and skills. Conversely, social categorization theory (Pelled et al., 1999; Bashir et al., 2021) suggests that pronounced age differences can also lead to subgroup formation, conflict, and reduced cohesion. The overall impact of age diversity on firm performance is thus theoretically ambiguous and likely to depend on contextual factors such as management quality, sectoral characteristics, and the inclusiveness of organisational practices (Backes-Gellner & Veen, 2013).

The age–productivity relationship can vary substantially across sectors and occupations, reflecting differences in production processes and skill requirements. Veen (2008) distinguishes between occupations in which productivity tends to decline with age, those with more age-neutral patterns, and those that may even benefit from an older workforce. While some studies examine the occupation-specific age–productivity nexus—for example, within management teams (Tanikawa, Kim & Jung, 2017), boards (Kagzi & Guha, 2018), and expert teams (Hu et al., 2024; Verwijs and Russo, 2023)—they generally focus on specific professions or narrow areas of economic activity. This study aims to contribute to a more systematic analysis of within-occupation age diversity by employing the ISO occupational group classification, grouping occupations into three broad categories: managerial workers, experts, and blue-collar workers.

The purpose of this paper is to study the relationship between the workforce age structure and firm productivity in Slovenia, distinguishing between the effects of age separation and age variety, and to examine how these effects differ across occupational groups and sectors. Our research objective is thus to investigate whether age diversity enhances or hinders firm productivity and if the productivity effects of age diversity differ across occupational groups and economic sectors. Using matched employer–employee data for

Slovenian firms with at least fifty employees between 2006 and 2016, we estimate a firm-level performance model with fixed-effects panel regression. In the model, firm performance is measured as value added per employee. By distinguishing between age separation and age variety and exploring heterogeneity across occupational groups and sectors, the study contributes to better understanding of the age diversity–performance nexus in an ageing European economy.

The remainder of this paper is structured as follows. Section 2 reviews the relevant theoretical and empirical literature on workforce age diversity and firm performance and outlines the research questions. Section 3 presents the methodological framework, including the data sources, variable definitions, and econometric approach. Section 4 reports the empirical results, first for the overall sample of firms and then across occupational groups and economic sectors. Section 5 concludes with a discussion of the main findings, policy implications, and directions for future research.

2 Literature review

In the context of an ageing society, understanding how age diversity within organisations affects their performance is of increasing importance for both researchers and policymakers. As demographic shifts lead to a growing share of older individuals in the labour force, firms are confronted with new challenges and opportunities related to workforce composition. The manner in which employees of different ages interact, share knowledge, and contribute to productivity has implications not only for firm outcomes but also for overall economic performance and competitiveness (Börsch-Supan, 2021). Firms are key nodes in translating demographic structures into economic output, and their ability to effectively utilise workers of different age groups can influence aggregate growth, innovation, and labour market inclusion (Aiyar et al., 2016).

Age diversity within firms can be beneficial for several reasons. A heterogeneous age structure may foster knowledge transfer and learning, as younger workers bring new ideas, technological skills, and flexibility, while older employees contribute with experience, tacit knowledge, and firm-specific expertise (Backes-Gellner & Veen, 2013). Moreover, age-diverse teams may be better equipped to understand and respond to diverse customer needs, reflecting the demographic composition of broader society. From a macroeconomic perspective, effective integration of workers of different ages can improve labour market efficiency, mitigate the economic consequences of population ageing, and sustain productivity growth (Börsch-Supan & Weiss, 2016).

However, age diversity may also have potential downsides for firm performance. Generational differences in work styles, communication patterns, and expectations may increase the potential for conflict and reduce team cohesion (Pelled, Eisenhardt & Xin, 1999). Older workers might be less adaptable to rapid technological change, while younger workers may lack the institutional knowledge or long-term perspective valued by the firm. Managing these differences requires effective human resource practices and an organisational culture that values inclusion and mutual respect. Without such support, the potential benefits of diversity can be offset by coordination costs, reduced

collaboration, and inefficiencies (Börsch-Supan, 2017; Parrotta, Pozzoli & Pytlikova, 2014). The relationship between age diversity and firm performance is thus complex and depends on factors such as management quality, industry characteristics, technological intensity, and the extent to which firms adopt age-inclusive practices (Posthuma & Campion, 2009). Understanding these dynamics is essential in an ageing society, as policies that encourage the productive use of age-diverse human capital can contribute to sustaining competitiveness and economic growth in the face of demographic change.

2.1 Theoretical perspectives

A higher share of older employees may enhance establishment-level productivity, as older workers typically possess greater experience, loyalty, and a stronger sense of quality and work ethic. Conversely, advanced age is often associated with lower levels of technical knowledge, creativity, innovativeness, flexibility, openness to new information, and physical as well as psychological resilience (Göbel & Zwick, 2012). Moreover, evidence from psychology and medical sciences suggests that "fluid" cognitive abilities—such as the capacity to process new information and the speed of problem-solving—tend to decline with age, whereas "crystallised" abilities, including vocabulary, verbal fluency, and the effective use of accumulated knowledge, improve over time and remain at a high functional level within typical working-age ranges (Skirbekk, 2008).

The literature on the consequences of workforce diversity draws primarily on two theoretical perspectives: social categorization theory and information/decision-making theory. Social categorization theory posits that individuals classify themselves and others into social groups based on salient demographic attributes such as age, gender, or ethnicity (Bashir et al., 2021). This categorization process can lead to in-group favouritism and out-group bias, which in turn undermine cohesion, trust, and collaboration in the workplace. Pronounced age differences may therefore trigger intergenerational tensions, hinder communication, and decrease team effectiveness (Pelled et al., 1999; Wegge et al., 2008). Empirical studies based on this theoretical perspective have often found negative associations between age diversity and performance outcomes, particularly in contexts where age polarization leads to conflict or stereotyping (De Meulenaere et al., 2016; Bashir et al., 2021).

By contrast, information/decision-making theory suggests that diversity enhances organisational performance by broadening the range of perspectives, skills, and experiences available for problem-solving and innovation (Van Knippenberg et al., 2004). Under this view, age variety is expected to yield positive outcomes, as employees of different ages bring distinct knowledge and experience that complement each other. In such settings, diversity facilitates creativity, adaptability, and collective learning—especially when managed within inclusive organisational cultures.

2.2 Conceptualizing age diversity: Separation and variety

Age diversity is a multidimensional construct that can be understood in conceptually distinct ways. Following Harrison and Klein (2007), it is important to distinguish between age separation and age variety, as they capture different structural properties of workforce composition. Age separation reflects differences along a continuous scale and measures how far apart employees are in terms of age, typically captured by the standard deviation of age within a firm. High age separation indicates a wide gap between the youngest and oldest employees, which may lead to the formation of distinct generational subgroups. Such polarization can intensify social categorization processes, as pronounced age gaps make intergenerational interaction and knowledge exchange more difficult, potentially leading to tensions and misunderstandings (De Meulenaere et al., 2016). Age variety, in contrast, refers to the extent to which employees are spread across multiple age categories and the degree to which these categories are balanced in size. It is usually measured by a heterogeneity index such as Blau's index, which captures the probability that two randomly selected individuals belong to different age categories. High age variety indicates that the workforce is composed of multiple age groups represented in relatively equal proportions, thereby creating opportunities for diverse perspectives, knowledge, and skills to contribute to performance outcomes (De Meulenaere et al., 2016).

Empirical studies consistently demonstrate that these two forms of age diversity—separation and variety—may have opposite implications for organizational outcomes. While age variety tends to promote learning, innovation, and problem-solving through informational and cognitive diversity, age separation may foster subgroup formation, conflict, and reduced cohesion (De Meulenaere et al., 2016). Recognizing this distinction allows for a more nuanced understanding of how age diversity relates to firm productivity. In line with this conceptual framework, our study operationalizes age diversity using two complementary indicators: (a) the standard deviation of employees' age to capture age separation and (b) the Blau index to measure age variety.

To test whether coordination costs outweigh complementarities we set the following hypotheses:

> **H1**: Greater age separation within a firm is negatively associated with labour productivity.
>
> **H2**: Greater age variety within a firm is positively associated with labour productivity.

2.3 Occupation and section specifics in age diversity – performance nexus

On the one hand, information/decision-making theory predicts stronger gains from diversity where tasks require problem-solving, judgment, and knowledge integration, or rely on experiential learning, coordination, and tacit knowledge transfer. On the other hand, social categorization costs are expected to be more salient in managerial roles, where authority, hierarchy, and strategic

consensus are critical and age-based subgrouping may disrupt cohesion (De Dreu & Weingart, 2003; Jehn, Northcraft & Neale, 1999). Tanikawa, Kim & Jung (2017) report that management team age diversity has a negative and significant impact on financial performance and that this effect is attenuated when the members of top management team are relatively older. Another study of direct effect of directors' age diversity on performance show that while the direct effect of age diversity of the management team on performance is not significant, it affects firm performance positively indirectly through higher effectiveness of management meetings (Sutarti Syakhroza, Diyanty & Dewo, 2021). Moreover, Kagzi and Guha (2018), analysing the role of demographic diversity on boards among Indian knowledge-intensive firms, show that age diversity in particular exerts a significant positive influence, whereas other individual diversity dimensions (such as education) may have negative effects. Although covered in smaller body of empirical literature, the age heterogeneity of experts is shown to be crucial for performance. In the literature, heterogeneity is often observed at the team level and studies report that when experts come from different age cohorts, teams tend to achieve higher performance, though they also warn of the potential for increased conflict (Hu et al., 2024 for scientific teams, Verwijs & Russo, 2023, for software teams). Veen (2008) identifies occupations such as bricklayer, tiler, and basic administrative roles as those in which productivity tends to decline with age, while professions such as bank or commercial clerks and electronic engineers exhibit more age-neutral productivity patterns. In contrast, occupations that rely heavily on accumulated experience and judgment—such as lawyers, professors, managers, medical doctors, or engineers—may even benefit from an older workforce. However, given that most sectors encompass a mix of occupations with both increasing and decreasing productivity potentials over the life course, it is not possible to formulate a clear hypothesis regarding systematic differences in relative productivity between age groups across sectors.

We thus hypothesise that:

> **H3**: The effect of workforce age diversity on labour productivity differs across occupational groups, reflecting differences in task complexity, knowledge intensity, and coordination requirements.

Göbel and Zwick (2012). argue that establishment age-productivity profiles might differ for various reasons. For example, the importance of physical strength and possibilities to compensate deficits in skills differ between sectors. They investigate differences in the age-productivity profiles between the manufacturing and services sectors. However, they find no significant differences in the age-productivity profiles between these sectors. Tong et al. (2024) report that labour force ageing has an adverse effect on the agricultural total factor productivity of farm households, and that this result remains robust after addressing endogeneity and substituting explanatory variables. Empirical evidence also points to sectoral differences in how age diversity relates to performance. In manufacturing, where production processes are often standardized and task interdependence is lower, moderate age diversity tends to have neutral or slightly positive effects, likely reflecting experience transfer and skill complementarity (Börsch-Supan & Weiss, 2016). In contrast,

in knowledge-intensive services, which rely heavily on collaboration, creativity, and rapid information processing, high age diversity may have ambiguous or even negative effects when not accompanied by inclusive management practices (Wegge et al., 2012). Evidence from agriculture is scarce, but studies on farm-level labour structures suggest that strong age imbalances within the workforce may hinder technological adoption and productivity growth (Raggi et al., 2013).

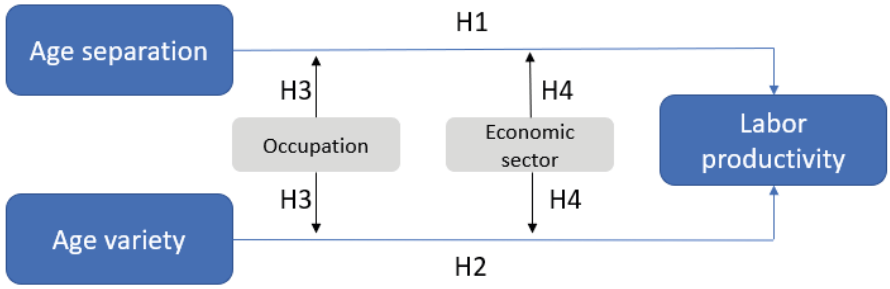
Based on this review our hypothesis is:

> **H4:** Age diversity is expected to be more strongly associated with higher labour productivity in sectors characterized by experience-based production processes.

3 Methodology

Our firm-level performance model, which uses labour productivity as a measure of firm performance, tests the above presented hypotheses and is represented by the following diagram of the empirical model.

Figure 1: Diagram of the empirical model



Source: Authors

We employ matched employer–employee data encompassing the entire population of Slovenian firms over the period 2006–2016. The matched dataset, obtained from the Statistical Office of the Republic of Slovenia, contains detailed information on the economically active population, including individuals' education, occupation, gender, age, and nationality, along with firm identifiers. These data are merged with firms' financial statements from the Agency of the Republic of Slovenia for Public Legal Records and Related Services (AJPES). The merge uses unique personal and firm identification codes. Since our focus is on within-occupation group age diversity, we consider only firms with 50 or more employees in our empirical model to ensure sufficient within-occupation variation and a sufficient number of observations within each occupational group. The resulting panel covers nearly 2,150 firms observed throughout the 2006–2016 period. The linkage of individual- and firm-level data enables the construction of key workforce composition variables, such as average employee age, age diversity (measured both in

terms of separation and variety), and other demographic characteristics (e.g., the share of women and the share of part-time employees). The firm-level regression model, which explains labour productivity as a measure of firm performance, is estimated for all firms with at least fifty employees.

We estimate a firm-level performance model using a fixed-effects panel data regression to examine the impact of age diversity on firm performance, measured as the natural logarithm of value added per employee (lnvaljt). The fixed-effects estimator was selected based on the Hausman test, which rejected the null hypothesis of no correlation between individual effects and the regressors. The baseline specification is given by:

$$Inval_{jt}=\beta_0+\beta_1 Age_{jt}+\beta_2 SD_{jt}+\beta_3 CV_{jt}+\beta_4 Blau_{jt}+X'_{jt}+\sum\beta_{5.k} d_industry_k+\sum\beta_{6.t}\, year_t+u_{jt} \quad (1)$$

where vector X' includes control variables, while subscripts *j, k* and t refer to firms, industries, and years, respectively. The role of employee age is captured through the average age of a firm's workforce (Age_{jt}), expressed in natural logarithmic form, and through three complementary measures of age diversity. Age separation is measured either in the form of standard deviation of employee age (SD_{jt}) or coefficient of variation (CV_{jt}), while the Blau index ($Blau_{jt}$) captures *age variety*, reflecting the probability that two randomly chosen employees belong to different age groups. The Blau index is defined as:

$$\text{Blau Index} = 1 - \sum_{i=1}^{k} p_i^2, \quad (2)$$

where p_i is the proportion of individuals in category *i*, and *k* is the total number of categories. The index ranges from 0 to (1 - 1/k). A value of 0 indicates perfect homogeneity, where all employees belong to the same age category, while the maximum is achieved when individuals are evenly distributed across all observed age categories and maximum diversity is reached. Additionally, we control for the share of female employees (*sh_Femaleit*) and share of part time workers (*sh_Parttimeit*).

Firm-level economic characteristics are controlled for by firm size, capital intensity, profitability, and export orientation. Firm size is measured by the number of employees ($Empl_{it}$) (in logarithmic form) and enters the model specification in both linear and quadratic form. Capital intensity ($Kint_{it}$) is defined as fixed assets per employee (log-transformed). Profitability is measured by the return on sales (ROS_{jt}), defined as the ratio of profit to sales, while export orientation ($EXorientation_{jt}$) is proxied by the share of revenues earned abroad. To mitigate potential endogeneity, all four firm-level control variables enter the regressions as lagged values. Year dummies (d_year_t) control for macroeconomic and institutional shocks, and industry dummies ($d_industry_k$) at the one-digit NACE level capture time-invariant sectoral effects.

Furthermore, to examine whether the effect of age diversity on firm performance varies across occupational groups and economic sectors, we extend the analysis by observing the role of average age and age diversity for selected occupational categories (managers, experts, and blue-collar workers) and estimating separate specifications for major sectors of economic activity (agriculture, manufacturing, and services).

Table 1: Descriptive statistics for firms with fifty or more employees

	Mean	**SD**
Value added per employee in €	37,371	38,203
Average age	40.9	4.1
Share of workers 50+	0.238	0.132
Age standard deviation (SD)	9.132	1.329
Age coefficient of variation (CV)	0.225	0.037
Average age - manager	45.2	6.2
Share of managers 50+	0.347	0.315
SD - manager	7.505	3.356
CV - manager	0.169	0.078
Average age - expert	39.3	5.7
Share of experts 50+	0.175	0.216
SD - expert	8.184	3.080
CV - expert	0.208	0.074
Average age - blue-collar	40.9	4.2
Share of blue-collars 50+	0.241	0.137
SD - blue-collar	9.102	1.414
CV - blue-collar	0.225	0.039
Blau index	0.956	0.019
No. of employees	214.4	491.4
Share of female workers	0.348	0.252
Share of part-time workers	0.031	0.124
Capital intensity in €	65,477	188,317
ROS	0.019	0.150
Export orientation	0.330	0.372
No. of observations	12,673	

Source: Authors

The descriptive statistics refer to a sample of over 2,150 firms with at least fifty employees. The average value added per employee amounts to €37,371, although the relatively large standard deviation (€38,203) indicates

considerable heterogeneity in labour productivity across firms. The mean age of employees within firms is 40.9 years, with a relatively low standard deviation (4.1), suggesting that the average workforce age does not vary substantially across firms. The within-firm standard deviation of employee age, averaging 9.1 years, points to a moderate degree of age separation within firms. The mean Blau index of 0.956 confirms a high level of workforce heterogeneity, implying relatively balanced distributions of employees across age group.

Managers are, on average, older than both experts and blue-collar workers, with an average age of approximately 45 years. Moreover, they exhibit the highest proportion of employees aged over 50 (around 35%), whereas among experts, the share of those over 50 is below 18%. Moreover, managers show the lowest age separation, both in terms of standard deviation and coefficient of variation. In contrast, blue-collar workers exhibit the highest age separation among the three broad occupational groups, while experts fall in between.

The average firm in the sample employs 214 workers, but the high dispersion (standard deviation of 491) reflects the presence of both medium-sized and very large firms in the sample. On average, 35 percent of employees are female, although the considerable standard deviation (0.25) suggests substantial variation in gender composition across firms. Part-time employment is relatively uncommon, representing only about 3 percent of total employment on average, albeit with notable variation across firms. Capital intensity averages around €65,500 per employee, with high variation (standard deviation of €188,317), indicating differences in firms' reliance on physical capital. The mean return on sales (ROS) is slightly above zero (0.02). Finally, firms' export orientation averages 0.33, indicating that approximately one third of total sales are derived from foreign markets. The relatively large variation in this indicator reflects the coexistence of predominantly domestically oriented firms and a smaller group of highly export-intensive firms.

4 Results and discussion

The results in table 2 show the fixed effects panel model estimates analysing the impact of age diversity on labour productivity measured as the natural logarithm of value added per employee across Slovenian firms with more than 50 employees.

Table 2: Fixed effects estimates of labour productivity model for Slovenian firms with more than 50 employees

Variables	(1) lnval	(2) lnval	(3) lnval	(4) lnval	(5) lnval
ln Age	-0.010***	-0.007**	-0.010***	-0.009***	-0.007**
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
SD (age separation)	0.013**			0.012**	

Variables	(1) lnval	(2) lnval	(3) lnval	(4) lnval	(5) lnval
	(0.005)			(0.005)	
CV (age separation)		0.481**			0.442**
		(0.204)			(0.205)
Blau (age variety)			0.088	0.554**	0.566**
			(0.114)	(0.240)	(0.240)
Sh_Female	-0.037	-0.036	-0.053	0.005	0.006
	(0.068)	(0.068)	(0.066)	(0.070)	(0.070)
Sh_Parttime	-0.097***	-0.098***	-0.101***	-0.096***	-0.096***
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
ln Empl(-1)	0.138***	0.137***	0.137***	0.139***	0.139***
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
ln Empl(-1)2	-0.016***	-0.016***	-0.016***	-0.017***	-0.017***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
ln Kintensity(-1)	0.043***	0.043***	0.043***	0.043***	0.043***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
ROS(-1)	0.290***	0.290***	0.291***	0.290***	0.290***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Ex_ orientation(-1)	0.127***	0.128***	0.133***	0.128***	0.129***
	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)
Constant	9.755*** 9.661***		9.793***	9.199***	9.098***
	(0.185)	(0.208)	(0.213)	(0.304)	(0.316)
Annual FE	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes
Observations	12,673	12,673	12,683	12,673	12,673
Number of firms	2,159	2,159	2,161	2,159	2,159
R2	0.084	0.084	0.084	0.085	0.085

Notes: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
Source: Authors

Based on the estimated fixed-effects panel regression model, the results indicate a consistent and meaningful relationship between workforce age composition and firm performance, measured as the natural logarithm of value added per employee. The Hausman test confirmed that the fixed-effects specification was appropriate, suggesting that unobserved firm heterogeneity

is correlated with the explanatory variables.

In the general model including all firms and industries (Table 2), the coefficient on the average employee age is negative and statistically significant across all model specifications. This finding implies that firms with older workforces tend to exhibit lower productivity, measured by value added per employee. In other words, an increase in average employee age is associated with a modest but statistically significant decline in productivity. This may reflect slower adaptation to technological change or higher labour costs among older workers (Backes-Gellner et al., 2011). Contrary to our hypothesis H1, the coefficients capturing age separation, are positive and statistically significant. This result is in line with findings of Backes-Gellner and Veen (2013), suggesting that greater heterogeneity in employee age contributes positively to firm productivity. The positive effect of age diversity can be interpreted as evidence of complementarities between younger and older employees, for instance through knowledge exchange, mentoring, and intergenerational learning within firms. As hypothesised, The Blau index, used as a measure of age variety, also shows a positive and significant association with value added per employee only in specifications in which age separation is controlled for. For companies with the same level of age separation, those with higher age variety are more productive. Consistent with prior studies in organisational settings (Horwitz & Horwitz, 2007), this positive association likely arises from the presence of multiple age groups, which fosters the exchange of diverse knowledge an skills, supporting innovation and problem-solving.

The control variables behave largely as expected. The impact of share of female employees is negative but statistically insignificant, while the role of share of part-time workers has a significant negative effect on productivity, suggesting that part-time work arrangements are associated with lower efficiency. Firm size, measured as the logarithm of employment and its squared term, displays the usual non-linear relationship: productivity increases with firm size but at a decreasing rate. Other firm characteristics—capital intensity, profitability (return on sales), and export orientation—all have positive and significant effects, confirming that more capital-intensive, profitable, and export-oriented firms are more productive.

When the analysis is disaggregated by occupational groups (Table 3), the results reveal interesting heterogeneity. For managers, age separation does not have a statistically significant impact on firm productivity, compared to some other empirical studies that provide ambiguous results (e.g. Tanikawa, Kim & Jung , 2017; Sutarti et al., 2021). By contrast, for experts (professionals), both measures of age separation—the standard deviation and the coefficient of variation—have positive and significant coefficients, suggesting that teams composed of younger and older experts tend to perform better, likely due to the combination of innovative capacity and experience. This is in line with reported findings in the literature (e.g. Li et al., 2021), showing that age heterogeneity of experts is very important for firm performance.

Among blue-collar workers, age separation also exerts a positive and statistically significant effect on productivity. This result may reflect the benefits of having teams that combine experienced workers with younger ones, improving coordination, task flexibility, and knowledge transfer on the

shop floor. Yet, at the same time, the average age of blue-collar workers is negatively associated with performance, indicating that an older production workforce may reduce productivity, though the effect is relatively small and not very statistically significant.

Table 3: Fixed effects estimates of labour productivity model for Slovenian firms with more than 50 employees, by occupational groups

Variables	**(1)** **lnval**	**(2)** **lnval**	**(3)** **lnval**	**(4)** **lnval**	**(5)** **lnval**	**(6)** **lnval**
Diversity measure	**SD**	**SD**	**SD**	**CV**	**CV**	**CV**
ln Age_ manager	0.001	0.001		0.001	0.001	
	(0.001)	(0.001)		(0.001)	(0.001)	
Share_ age50_ manager			0.032			0.036
			(0.024)			(0.023)
Age separation _manager	0.002	0.002	0.002	0.101	0.103	0.085
	(0.002)	(0.002)	(0.002)	(0.079)	(0.079)	(0.077)
ln Age_ expert	0.000	0.000		0.001	0.001	
	(0.002)	(0.002)		(0.002)	(0.002)	
Share_ age50_ expert			0.001			0.011
			(0.035)			(0.034)
Age separation _expert	0.004**	0.004**	0.004*	0.143*	0.146**	0.136*
	(0.002)	(0.002)	(0.002)	(0.074)	(0.074)	(0.075)
ln Age_blue-collar	-0.006*	-0.006*		-0.004	-0.004	
	(0.003)	(0.003)		(0.004)	(0.004)	
Share_ age50_blue-collar			-0.078			-0.036
			(0.082)			(0.082)

Variables	(1) Inval	(2) Inval	(3) Inval	(4) Inval	(5) Inval	(6) Inval
Age separation _blue-collar	0.012**	0.014**	0.016***	0.443*	0.495*	0.570***
	(0.006)	(0.007)	(0.006)	(0.255)	(0.279)	(0.202)
Blau index		-0.724			-0.497	
		(1.098)			(1.085)	
Sh_Female	0.074	0.068	0.065	0.072	0.068	0.069
	(0.100)	(0.101)	(0.100)	(0.100)	(0.101)	(0.100)
Sh_Parttime	-0.105***	-0.105***	-0.107***	-0.106***	-0.106***	-0.106***
	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)
ln Empl(-1)	0.160***	0.158***	0.160***	0.159***	0.158***	0.159***
	(0.048)	(0.048)	(0.048)	(0.048)	(0.048)	(0.048)
ln Empl(-1)2	-0.018***	-0.018***	-0.018***	-0.018***	-0.018***	-0.018***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
ln Kintensity(-1)	0.048***	0.048***	0.048***	0.048***	0.048***	0.048***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
ROS(-1)	0.276***	0.276***	0.276***	0.276***	0.276***	0.275***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Ex_ orientation(-1)	0.163***	0.163***	0.162***	0.164***	0.164***	0.162***
	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)
Constant	9.446***	10.126***	9.224***	9.338***	9.794***	9.232***
	(0.259)	(1.065)	(0.198)	(0.287)	(1.038)	(0.197)
Annual FE	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
Observations	8,104	8,104	8,104	8,104	8,104	8,104
Number of firms	1,353	1,353	1,353	1,353	1,353	1,353
R-squared	0.090	0.090	0.090	0.090	0.090	0.090

Notes: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
Source: Authors

When considering differences across industries, age separation within all three occupational groups exerts a positive impact on productivity in manufacturing. Contrary to Backes-Gellner and Veen (2013), this implies that having employees of different ages is beneficial across occupations in

manufacturing firms, likely because it facilitates the transfer of knowledge and experience. In the primary sector, age separation is relevant only for experts, highlighting the importance of combining younger and older professionals to exchange expertise and enhance performance. By contrast, in services and high-technology sectors, age separation is not significant for any occupational group or is even slightly negative, indicating that other factors are likely more important for productivity in technology-intensive environments and service-based operations. Furthermore, once age separation is accounted for, age variety—as measured by the Blau index—does not have a significant additional effect across occupations or industries.

Our findings consistently indicate that age diversity enhances firm productivity, but the strength and significance of this relationship vary across occupational groups and sectors. The positive effects are strongest among experts and blue-collar workers in manufacturing, while less significant effects are observed for managers or in service and high-technology sectors. Although a higher average age of employees is associated with slightly lower productivity, greater diversity in age composition within firms appears to mitigate this negative effect and, in many cases, turn it into a net positive outcome. An exception is observed in the agriculture sector, where a higher average age among workers in managerial positions shows a positive association with productivity. While the estimated coefficients are quantitatively modest, they imply non-negligible productivity gains from fostering moderate levels of age heterogeneity. Overall, the results support the view that age-diverse teams can generate productivity advantages through complementary skills, intergenerational collaboration, and experience sharing across age cohorts, as found in Wegge et al. (2012).

Table 4: Fixed effects estimates of productivity model for Slovenian firms with more than 50 employees, by occupational groups and economic sector

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
	lnval	**lnval**	**lnval**	**lnval**	**lnval**	**lnval**	**lnval**	**lnval**
Diversity measure	**SD**	**CV**	**SD**	**CV**	**SD**	**CV**	**SD**	**CV**
Sector	Agriculture		Manufacturing		Services		High-tech	
ln Age_manager	0.022**	0.025***	0.001	0.001	0.001	0.000	-0.011	-0.013*
	(0.009)	(0.009)	(0.002)	(0.002)	(0.003)	(0.003)	(0.007)	(0.007)
Age separation _manager	0.017	0.793	0.004**	0.190**	-0.003	-0.117	-0.014	-0.606
	(0.015)	(0.707)	(0.002)	(0.096)	(0.003)	(0.147)	(0.009)	(0.379)
ln Age_expert	-0.001	0.006	0.000	0.001	-0.001	-0.001	0.015	0.017
	(0.008)	(0.007)	(0.002)	(0.002)	(0.003)	(0.003)	(0.013)	(0.013)
Age separation _expert	0.038***	1.753***	0.005**	0.189**	-0.001	-0.056	0.005	0.313
	(0.012)	(0.483)	(0.002)	(0.090)	(0.004)	(0.137)	(0.021)	(0.767)

Variables	(1) Inval	(2) Inval	(3) Inval	(4) Inval	(5) Inval	(6) Inval	(7) Inval	(8) Inval
Diversity measure	**SD**	**CV**	**SD**	**CV**	**SD**	**CV**	**SD**	**CV**
ln Age _blue-collar	-0.030	-0.030	0.000	0.003	-0.008	-0.007	-0.011	-0.015
	(0.031)	(0.038)	(0.005)	(0.006)	(0.006)	(0.006)	(0.011)	(0.011)
Age separation _blue-collar	-0.025	-0.700	0.021**	0.696*	0.001	0.099	-0.023	-0.807
	(0.045)	(1.881)	(0.010)	(0.408)	(0.010)	(0.403)	(0.015)	(0.578)
Blau index	-6.417	-6.755	0.853	1.307	-1.077	-1.136	3.021	2.870
	(6.361)	(6.158)	(1.599)	(1.580)	(1.661)	(1.651)	(3.000)	(3.035)
Sh_Female	0.532	0.669	0.061	0.063	0.212	0.213	-0.436	-0.441
	(0.902)	(0.892)	(0.133)	(0.133)	(0.162)	(0.162)	(0.471)	(0.469)
Sh_Parttime	-0.142	-0.149	-0.101***	-0.102***	-0.266**	-0.266**	-0.017	-0.018
	(0.162)	(0.160)	(0.035)	(0.035)	(0.106)	(0.106)	(0.192)	(0.192)
ln Empl(-1)	-1.231	-1.364	0.246***	0.246***	0.012	0.012	0.106	0.112
	(0.851)	(0.847)	(0.066)	(0.066)	(0.075)	(0.075)	(0.121)	(0.121)
ln Empl(-1)2	0.097	0.109	-0.023***	-0.023***	-0.004	-0.004	-0.006	-0.006
	(0.083)	(0.083)	(0.007)	(0.007)	(0.008)	(0.008)	(0.016)	(0.016)
ln Kintensity(-1)	0.133	0.100	0.042***	0.042***	0.057***	0.057***	-0.007	-0.008
	(0.122)	(0.122)	(0.008)	(0.008)	(0.012)	(0.012)	(0.025)	(0.025)
ROS(-1)	0.019	0.034	0.166***	0.166***	0.405***	0.405***	0.955***	0.957***
	(0.142)	(0.141)	(0.031)	(0.031)	(0.031)	(0.031)	(0.055)	(0.055)
Ex_ orientation(-1)	-0.031	-0.047	0.124**	0.125**	0.214**	0.214**	-0.227	-0.213
	(0.243)	(0.241)	(0.061)	(0.061)	(0.101)	(0.101)	(0.235)	(0.235)
Constant	18.555***	19.027***	7.999***	7.405***	11.245***	11.297***	8.511***	8.776***
	(6.913)	(6.778)	(1.547)	(1.503)	(1.581)	(1.552)	(2.868)	(2.855)
Observations	190	190	5,290	5,290	2,624	2,624	408	408
Number of firms	29	29	869	869	482	482	70	70
R-squared	0.352	0.368	0.088	0.088	0.121	0.121	0.565	0.565

Notes: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1annual and industry FE included.
Source: Authors

5 Conclusions

The findings of this study demonstrate that age diversity within firms constitutes an important, yet often underappreciated, source of productive strength. While firms with older workforces on average exhibit lower labour productivity,

greater age heterogeneity consistently shows a positive association with firm performance. This suggests that when younger and older employees work together, complementarities in experience, skills, and perspectives may outweigh potential coordination costs.

Contrary to expectations derived from social categorization theory, both measures of age separation (standard deviation and coefficient of variation) show positive and statistically significant effects in the baseline models, which contradicts our hypothesis H1. This indicates that wider age dispersion within firms may facilitate beneficial knowledge exchange and intergenerational learning rather than generate disruptive subgroup dynamics. The Blau index exhibits a positive and significant coefficient in specifications that control for age separation, suggesting that balanced representation of multiple age groups contributes to higher productivity when polarization effects are accounted for. This finding is consistent with information/decision-making theory, which emphasizes the benefits of cognitive and experiential diversity. Our hypothesis H2 is thus conditionally supported. Hypothesis H3, predicting heterogeneity of effects across occupational groups, is supported. The results clearly show that the productivity effects of age diversity differ by occupation. Age separation is not significant among managers but is positive and significant among experts and blue-collar workers. This pattern suggests that diversity yields the greatest benefits in task environments characterized by experiential learning, technical complementarity, and operational interdependence. Hypothesis H4, which expected stronger positive effects of age diversity in experience-based sectors, receives partial support. The positive impact of age separation is most pronounced in low- and medium-technology manufacturing and, to a more limited extent, in parts of the primary sector. However, the effects are weak or insignificant in services and high-technology industries. Taken together, the results highlight that age diversity is not universally beneficial or harmful; rather, its productivity effects depend on how age differences interact with task structure, occupational composition, and sectoral characteristics.

From a policy standpoint, these results imply that age diversity should not be viewed as only a challenge arising from demographic ageing, but also as an asset that firms and societies can actively leverage. Firms that recognize and cultivate the strengths of age-diverse workforces—by promoting collaboration across generations, designing inclusive human resource practices, and valuing the contributions of older employees—stand to gain in terms of innovation, stability, and performance. Older workers are particularly valuable when embedded in mixed-age teams, where their institutional memory, problem-solving skills, and mentoring capacity can be effectively combined with the creativity and technological fluency of younger colleagues. Policy interventions should therefore focus on supporting organisational strategies that enhance intergenerational cooperation. This includes promoting mentoring and reverse mentoring, supporting lifelong learning for older workers, and encouraging flexible work arrangements that enable longer, more productive careers. By fostering a culture that values diversity across the life course, both managers and policymakers can help turn demographic ageing into an opportunity for sustained competitiveness and inclusive growth.

Administrative nature of the data does not allow direct observation of task characteristics, team structures, or age-inclusive human resource practices. Consequently, while the results are consistent with mechanisms such as knowledge transfer and intergenerational complementarities, these channels cannot be tested explicitly. Future research should continue to examine these mechanisms through which intergenerational collaboration enhances performance, explore how management practices and technological change shape these effects, and assess the transferability of these findings to other institutional and cultural contexts.

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Fiscal Resilience of CEFTA Countries: Macroeconomic Shocks and Fiscal Structural Factors

Original scientific paper

Biljana Srdić Gojković[1], Milenko Krajišnik[2], Dragan Gligorić[3], Sanja Popović[4]

ABSTRACT

This paper analyses fiscal resilience in Central European Free Trde Ageement (CEFTA) member countries by examining how fiscal health responds to major macroeconomic shocks and key fiscal and macroeconomic variables such as public debt dynamics, revenue capacity, expenditure structure, and economic activity over the period 2004–2024. The empirical analysis is based on a constructed composite fiscal health index that captures both stock and flow dimensions of public finances and employs a Dynamic Common Correlated Effects Autoregressive Distributed Lag (DCCE-ARDL) panel model, incorporating relevant macroeconomic and fiscal control variables as well as major external economic shocks. The evolution of the Fiscal Health Index reveals pronounced cross-country differences in fiscal resilience among CEFTA members, reflected in differences in volatility, crisis-related declines, and recovery over time. The results from DCCE-ARDL panel model indicate the existence of a stable long-run relationship between fiscal health and its

1 *Assistant Professor, University of Banja Luka, Faculty of Economics, Majke Jugovića 4, 78000 Banja Luka, Bosnia and Herzegovina. Scientific affiliation: international economics. Phone: 003876598335, e-mail: biljana.srdic-gojkovic@ef.unibl.org*

2 *Full Professor, University of Banja Luka, Faculty of Economics, Majke Jugovića 4, 78000 Banja Luka, Bosnia and Herzegovina. Scientific affiliation: international economics. Phone: 0038765546019, e-mail: milenko.krajisnik@ef.unibl.org.*

3 *Associate Professor, University of Banja Luka, Faculty of Economics, Majke Jugovića 4, 78000 Banja Luka, Bosnia and Herzegovina. Scientific affiliation: international economics, Phone: 0038765443355. E-mail: dragan.gligoric@ef.unibl.org*

4 *MSc student, University of Banja Luka, Faculty of Economics, Banja Luka, Majke Jugovića 4, 78000 Banja Luka, Bosnia and Herzegovina; Head of Economic Policy and Public Finances Department, Fiscal Council of the Republic of Srpska, Trg Republike 8/XIII Banja Luka, 0038765495256. E-mail: sanja.popovic@fiskalnisavjetrs.org*

determinants, with fiscal outcomes exhibiting strong persistence but gradual adjustment following shocks. Empirical findings suggest that while exposure to global economic shocks matters, fiscal resilience in CEFTA countries is primarily determined by internal fiscal structures, particularly revenue capacity and debt servicing burdens.

***Keywords**: Fiscal resilience, Fiscal health, Macroeconomic shocks, DCCE-ARDL, CEFTA countries*

***JEL classification**: C33, F15, H62, H63*

1 Introduction

The concept of fiscal resilience has become a central topic in contemporary macroeconomic and fiscal theory, particularly following the global financial crisis of 2008 and the disruptions caused by the COVID-19 pandemic. A major additional challenge was the energy crisis that emerged after the outbreak of the war in Ukraine in 2022, when the sharp increase in energy prices led to the inflationary pressures and rising budgetary expenditure. All these developments raise the legitimate question of whether countries are capable of maintaining fiscal health and remaining resilient to such external shocks over a short period of time. In a global context characterized by fiscal pressures, population ageing, and accelerated economic transitions, the capacity of countries to mobilize stable and sustainable tax revenues represents the key pillar for maintaining macroeconomic and social stability. The analysis of fiscal resilience and fiscal health during these shocks enables the identification of strengths and weaknesses of fiscal systems in CEFTA countries, which is crucial for designing sustainable policies, strengthening fiscal resilience, and building adequate buffers for future economic and external shocks. The research hypothesis states: The fiscal health indicator enables the assessment of the level of fiscal resilience, while the analysis of its determinants identifies structural fiscal factors that contribute to the greater or lesser vulnerability of CEFTA countries to external shocks.

The term fiscally resilient (less vulnerable) countries refers to countries that, following an external shock or a crisis caused by external disturbances, are able to stabilize public finances relatively quickly and restore them to pre-crisis levels. In contrast, fiscally non-resilient countries are characterized by a stronger negative response to external shocks, reflected in higher growth of budget deficits and public debt, as well as slower recovery of public finances and overall economic activity. Therefore, it is particularly interesting to analyse fiscal resilience in CEFTA countries, not only because of their size and level of development, but also due to their limited fiscal space and pronounced vulnerability to external shocks.

The paper is structured as follows: Section 2 presents the literature review; Section 3 describes the applied methodology and construction of the fiscal health index; Section 4 presents empirical data analysis; Section 5 reports

and discusses the empirical results of the DCCE-ARDL analysis; and the final section provides concluding remarks and policy implications.

2 Literature review

Fiscal health is an indicator of fiscal resilience, as it represents the comprehensive assessment of a country's ability to maintain sustainable public finances over time and absorb economic shocks (Afonso, 2005; International Monetary Fund, 2015). Fiscal health is a complex measure that provides a comprehensive picture of fiscal conditions and resilience. Fiscally healthy economies are characterized by sustainable public debt, stable revenues, controlled expenditures, and sufficient fiscal space which enables them to absorb negative economic shocks without destabilizing public finances. Stable public finances and strong fiscal health significantly contribute to fiscal resilience by reducing the risk of fiscal crises and increasing the government's capacity to respond adequately to economic shocks. When revenues are stable, expenditures are controlled, and public debt is sustainable, the government has sufficient fiscal space to respond in times of crisis. Fiscal health captures the current level of a country's fiscal condition, while fiscal resilience reflects its dynamic capacity to adjust to shocks. Fiscal resilience implies not only short-term stability but also the ability of the country to preserve sound public finances throughout economic cycles. In this context, fiscal health represents a key determinant of fiscal resilience, as it enables governments to maintain stable public finances and respond effectively to economic shocks. According to the International Monetary Fund (IMF), fiscal resilience implies the existence of adequate fiscal space that allows governments to respond to crises without jeopardizing solvency (International Monetary Fund, 2005). The IMF emphasizes that it is difficult to assess the extent of fiscal manoeuvring room available to national policymakers for increasing spending or reducing taxes, making this a critical issue during periods of economic downturn, when governments are expected to stimulate the economy. Nevertheless, the IMF emphasizes that countries with strong fiscal health are better able to implement countercyclical policies without jeopardizing solvency (International Monetary Fund, 2015).

According to Mankiw (1987), fiscal resilience is associated with the management of government revenues and expenditures, with public spending being maintained at an optimal level achieved through a combination of fiscal and monetary policies. Blanchard and Das (2017) define fiscal resilience in terms of how long current fiscal policy can be sustained without creating future debt problems. Some authors define fiscal resilience as the ability of the budgetary system to service all debt obligations and recover from the effects of external shocks. Salamaliki and Venetis (2024), using evidence from OECD countries, analyse how fiscal health, as a measure of fiscal space, affects fiscal responses during crises. They introduce a nonlinear measure of fiscal health that simultaneously considers public debt and budget deficits.

Empirical studies show that countries with stronger fiscal health face lower financing costs, which increases their fiscal flexibility and capacity to respond to shocks (Reinhart and Rogoff, 2010; Alesina et al., 2018). Countries with weaker

fiscal health tend to experience fiscal crises earlier, confirming its preventive role as an indicator of fiscal resilience (Kaminsky et al., 2004). Bernardini and Forni (2020) found that during adverse, crisis periods, limited fiscal space is accompanied by more pronounced reductions in public expenditures and higher fiscal stress, exacerbating the negative effects of the crisis. Aizenman and Jinjarak (2011) emphasize that, in terms of fiscal resilience, focusing the analysis on the budget balance is justified because persistent fiscal deficits significantly contribute to the erosion of fiscal resilience and may limit the effectiveness of fiscal policy responses during crises. Within their analysis, Jordà et al. (2016) demonstrated that entering a crisis with a high level of debt is associated with much deeper recessions and slower recovery. Based on their findings, high initial level of debt before the outbreak of a crisis, and thus limited fiscal space, constrains a country's capacity to implement stabilization policies and return to a growth trajectory after significant downturns caused by crises. Fiscal resilience is also defined as the ability of a country to absorb external shocks, maintain stability in public finances, and timely restore its fiscal position without jeopardizing the long-term sustainability of debt (Lobont et al., 2025).

The role of fiscal policy in stabilizing economies during crises has been widely analysed, particularly following major global disruptions such as the 2008 financial crisis and the COVID-19 pandemic. Empirical evidence indicates that well-targeted government spending can counteract economic downturns by stimulating demand, preserving employment, and maintaining essential public services (Rosenthal & Kouzmin, 1997). Government expenditure remains the key instrument for mitigating the economic effects of shocks, especially during periods of heightened volatility (Larch et al., 2025). Extensive literature has explored the role of fiscal policy in stabilizing economies during crises, highlighting the multi-layered relationship between public spending and economic recovery (Ding et al., 2024; Marioli et al., 2023). Empirical studies have emphasized that government spending can act as an effective fiscal stimulus, significantly promoting economic recovery during recessions (Güzel & Çetin, 2016).

Compaoré et al. (2020) analysed whether the diversification of tax revenues enhances resilience to fiscal risks, using a new tax revenue diversification index for 127 countries over the period 2000–2015. Their findings indicate that greater diversification of tax revenues strengthens fiscal resilience. Yohou (2023) examined the impact of tax reforms on fiscal space through a panel analysis of developing countries between 1990 and 2016, with results confirming that effective tax reforms can significantly expand fiscal space and enhance fiscal resilience. Riblier (2023) investigated, using historical data from the United States, how public debt servicing affects fiscal policy and fiscal space. The study shows that high levels of debt repayment reduce the effectiveness of fiscal policy, particularly in response to shocks, as debt service constitutes a fiscal burden that limits the government's capacity to issue new debt. Afshan and Vien (2024), through an analysis of fiscal health at local government levels, concluded that fiscal health - as a measure of the strength and stability of public finances - can act as a driver of economic development, whereas GDP growth alone is not necessarily a direct predictor of improvements in fiscal health and resilience. Kurt (2012) analysed the

determinants of budget balances for 25 European countries using fiscal and macroeconomic indicators over the period 1998–2008, explicitly considering the effects of crises. The results indicate that increases in public revenues and inflation contribute to an improved budget balance, while rising public expenditures and crisis periods significantly worsen fiscal outcomes, confirming the central role of the revenue side and fiscal shocks in shaping budgetary performance.

In circumstances of fiscal instability and reduced resilience to crisis-induced shocks, the IMF emphasize the importance of fiscal rules, such as limits on public debt and deficits, as instruments of fiscal resilience (International Monetary Fund, 2022). Generally, countries that had implemented certain fiscal frameworks over a prolonged period prior to crises tended to be more resilient during crises. A country's initial fiscal position, particularly the level of public debt and deficits, significantly affects its capacity to implement stimulus measures and recovery policies. Governments with higher debt burdens tend to face more pronounced trade-offs between current, stimulus public spending and long-term fiscal sustainability. Numerous authors highlight that fiscal adjustment measures during crises can have varying effects depending on the level of public debt, monetary policy response, and the degree of economic openness. While countries with fiscal space can use expansionary fiscal policy as a stabilization mechanism, highly indebted countries often lack this capacity and are frequently compelled to adopt austerity measures.

Although numerous studies have examined fiscal stability in Western Balkan countries (Krajišnik et al., 2021), there are no studies that focus exclusively on CEFTA countries as a group, particularly in the context of measuring fiscal resilience. Therefore, it is of particular importance to analyse fiscal resilience in CEFTA countries, identify its determinants, and map relevant segments of economic policy that enable the design of adequate measures to preserve fiscal health and strengthen resilience to shocks.

3 Methodology

The empirical analysis employs the Dynamic Common Correlated Effects Autoregressive Distributed Lag model, implemented using the xtdcce2 command in Stata (Ditzen, 2018; Ditzen 2021). This methodology is particularly suitable for macroeconomic panel data that exhibit cross-sectional dependence, heterogeneous dynamics, and mixed orders of integration as well as unbalanced panels, as detected in the previous section of the paper.

Macroeconomic and fiscal variables across countries are often affected by common shocks, regional spillovers, and global economic conditions, leading to cross-sectional dependence in the error structure. Ignoring this dependence may result in biased and inconsistent estimates (Chudik and Pesaran, 2015). In addition, fiscal variables often differ in their degree of persistence, with some series being stationary in levels and others becoming stationary only after first differencing. The ARDL framework naturally accommodates this feature by allowing a combination of I(0) and I(1) variables within the same model. By extending the ARDL approach to a panel setting and augmenting it with cross-sectional averages, the DCCE-ARDL model is able to capture both

heterogeneous dynamics and unobserved common shocks.

Following Ditzen (2021), the baseline model is specified as a cross-sectionally augmented ARDL (p_y, p_x) process:

$$y_{i,t} = \mu_i + \sum_{l=1}^{p_y} \lambda_{l,i} y_{i,t-l} + \sum_{l=0}^{p_x} \beta_{l,i} x_{i,t-l} + \sum_{l=0}^{p} \boldsymbol{\gamma}'_{i,l} \bar{\mathbf{z}}_{t-l} + e_{i,t} \quad (1)$$

where yi,t denotes fiscal health, measured by the composite fiscal indicator used in the empirical analysis, and reflects the overall sustainability and resilience of public finances. The vector xi,t-l represents a set of macroeconomic and fiscal explanatory variables entering the model with distributed lags, allowing for delayed effects of economic activity, public debt dynamics, and budgetary performance on fiscal health. The term $\bar{z}_{t-l}$ denotes lagged cross-sectional averages of the dependent and explanatory variables and is included to capture the influence of unobserved common shocks, such as global economic conditions, regional spillovers or financial cycles affecting all countries in the panel.

Rewriting the model in error-correction form yields:

$$\Delta y_{i,t} = \mu_i - \phi_i (y_{i,t-1} - \theta_{1,i} x_{i,t-1}) + \beta_{0,i} \Delta x_{i,t} + \sum_{l=0}^{p_T} \boldsymbol{\gamma}'_{i,l} \bar{\mathbf{z}}_{t-l} + e_{i,t} \quad (2)$$

where ϕ_i denotes the error-correction (adjustment) coefficient. A negative and statistically significant value of ϕ_i indicates the presence of a stable long-run relationship between fiscal health and its determinants, as deviations from the long-run equilibrium - defined by the underlying DCCE -ARDL specification - are gradually corrected over time.

The DCCE-ARDL specification allows for a clear separation between short-run dynamics and long-run equilibrium relationships. Short-run dynamics are captured through first differences of the regressors and the lagged dependent variable, as reflected in the error-correction representation, thereby accounting for persistence and adjustment dynamics in fiscal outcomes. Long-run coefficients describe equilibrium relationships implied by the underlying DCCE-ARDL structure and reflect structural fiscal characteristics, such as revenue capacity or debt servicing obligations. Estimation is conducted within a heterogeneous DCCE-ARDL framework, allowing slope coefficients to differ across countries. As a result, panel-level long-run effects are interpreted as averages of country-specific coefficients, consistent with a mean-group type interpretation. This approach is appropriate given the heterogeneity in fiscal institutions and economic structures among CEFTA countries and avoids imposing potentially restrictive homogeneity assumptions, while remaining consistent in the presence of cross-sectional dependence.

Overall, the DCCE-ARDL methodology provides a flexible and robust framework for analyzing fiscal health dynamics, as it simultaneously accounts for cross-sectional dependence, heterogeneous adjustment processes, and mixed integration properties of the data.

4 Empirical data and analysis

In order to estimate the impact of macroeconomic and fiscal variables on fiscal resilience, a set of relevant independent variables is employed. The analysis covers the period from 2004 to 2024 and is conducted for six CEFTA countries: Albania, Bosnia and Herzegovina, Moldova, Montenegro, North Macedonia, and Serbia. The selected time span is chosen to maximize the length of the available data series. Due to data limitations, Kosovo is excluded from the analysis. For some countries and specific years, data on mandatory expenditure share, tax revenue share, and public debt service are not available. Consequently, the panel becomes unbalanced when these variables are included in the model. All variables used in the empirical analysis are summarized in Table 1.

Table 1: Definition of variables and measurement

Variable	Type of variable	Code	Method of measurement	Data source
General government gross debt	Dependent	gdebt	General government gross debt, % of GDP	International Monetary Fund - World Economic Outlook
General government net lending/ borrowing (budget balance)	Dependent	bbalance	General government net lending/borrowing, % of GDP	International Monetary Fund - World Economic Outlook
Fiscal health index	Dependent	fhealth	Composite fiscal health index based on budget balance and public debt indicators (with thresholds of -7% for the budget balance and 100% of GDP for public debt)	Authors calculations
Fiscal health index (alternative thresholds)	Dependent	Fhealth2	Composite fiscal health index based on budget balance and public debt indicators (with thresholds of -3% for the budget balance and 60% of GDP for public debt)	Authors calculations

Variable	Type of variable	Code	Method of measurement	Data source
Real GDP growth	Independent	rgdp	Gross domestic product, constant prices, annual percent change	International Monetary Fund - World Economic Outlook
Inflation	Independent	infl	Inflation, average consumer prices, annual percent change	International Monetary Fund - World Economic Outlook
General government final consumption expenditure	Independent	gov_ con_ finexp	General government final consumption expenditure, % of GDP	World Bank – World Development Indicators
Trade openness	Independent	trade_ open	Sum of exports and imports, % of GDP	World Bank – World Development Indicators
Intra CEFTA trade	Independent	intra_ cefta	Sum of exports and imports within the CEFTA region, % GDP	World Bank - World Integrated Trade Solution (WITS)
Mandatory expenditure share	Independent	mand_ exp_ share	Mandatory expenditure, % of total government expenditure	Authors calculation, based on IMF data- Government Finance Statistics
Tax revenue share	Independent	tax_rev_ share	Tax revenue, % of total government revenue	Authors calculation, based on IMF data- Government Finance Statistics
Public and publicly guaranteed debt service	Independent	pdebt_ service	Public and publicly guaranteed debt service, % of GNI	World Bank – World Development Indicators
Interest expenses	Independent	interest_ exp	Interest paid on public debt, % GDP	Authors calculation, based on IMF data - World Economic Outlook

Variable	Type of variable	Code	Method of measurement	Data source
Government Effectiveness	Independent	gov_ef	Government Effectiveness: Estimate, country's score on the aggregate indicator, in units of a standard normal distribution, i.e. ranging from approximately -2.5 to 2.5, where higher values indicate more effective government	World bank: Worldwide Governance Indicators (WGI)
Political Stability and Absence of Violence/ Terroris	Independent	pol_stab	Political Stability and Absence of Violence/ Terroris: Estimate, country's score on the aggregate indicator, in units of a standard normal distribution, i.e. ranging from approximately -2.5 to 2.5, where higher values indicate greater political stability	World bank: Worldwide Governance Indicators (WGI)
Control of Corruption	Independent	corup_ contol	Control of Corruption: Estimate, country's score on the aggregate indicator, in units of a standard normal distribution, i.e. ranging from approximately -2.5 to 2.5, where higher values indicate greater control of corruption	World bank: Worldwide Governance Indicators (WGI)

Variable	Type of variable	Code	Method of measurement	Data source
Dummy for Global Economic Crisis 2008	Independent	d2008	Takes the value of 1 for the year 2008, when Global Economic Crisis occurred, and 0 otherwise.	-
Dummy for COVID-19 crisis	Independent	D2020	Takes the value of 1 for the year 2020, when the COVID 19 pandemic had a major economic impact, and 0 otherwise.	-

Source: Authors

To measure fiscal resilience, the fiscal health index is calculated based on the methodology proposed by Salamaliki and Venetis (2024). The fiscal health indicator, following the previously mentioned study, is constructed as a weighted sum of two indicators: the public debt score and the average budget deficit score (for the current and two preceding years), with public debt and the average budget deficit expressed as percentages of GDP. The objective of assessing fiscal resilience based on the composite fiscal health indicator is to capture both the stock and flow dimensions of a country's fiscal position, incorporating nonlinear penalization of unfavourable fiscal outcomes. While most existing empirical studies on fiscal resilience have emphasized the level of public debt relative to GDP, the composite fiscal health indicator provides a comprehensive picture of the condition, soundness, and resilience of public finances, as it simultaneously accounts for both public debt and budget deficits. The three-year average of budget deficits indicates persistent fiscal imbalances and reflects the level of structural fiscal discipline.

According to the described methodology, fiscal health is expressed as a score variable with a minimum value of 0 and a maximum value of 100, where higher values indicate better fiscal conditions. The overall fiscal health score is calculated using the following formula:

$$Fiscal\ health = w*debt\ score + (1-w)*\ deficit\ score \quad (3)$$

where the weights w and (1 − w) are determined in line with the values used in the calculation of the Heritage Economic Freedom Index, namely 20% for public debt and 80% for the average budget deficit, reflecting the greater short-term impact of deficits on fiscal stability, while still accounting for the accumulated burden of debt. This weighting emphasizes current fiscal pressures without ignoring long-term obligations. The public debt score and the average budget deficit score are calculated using the following nonlinear equations:

$$\text{debt score} = \begin{cases} 0 & , \quad x \geq \alpha \\ 100 - \left(\frac{100}{\alpha^{\beta}}\right) \cdot x^{\beta} & , \quad 0 \leq x < \alpha \end{cases} \tag{4a}$$

$$\text{deficit score} = \begin{cases} 100 & , \quad x \geq 0 \\ 100 - \left(\frac{100}{|\alpha|^{\beta}}\right) \cdot |x|^{\beta} & , \quad -\alpha \leq x < 0 \\ 0 & , \quad x < -\alpha \end{cases} \tag{4b}$$

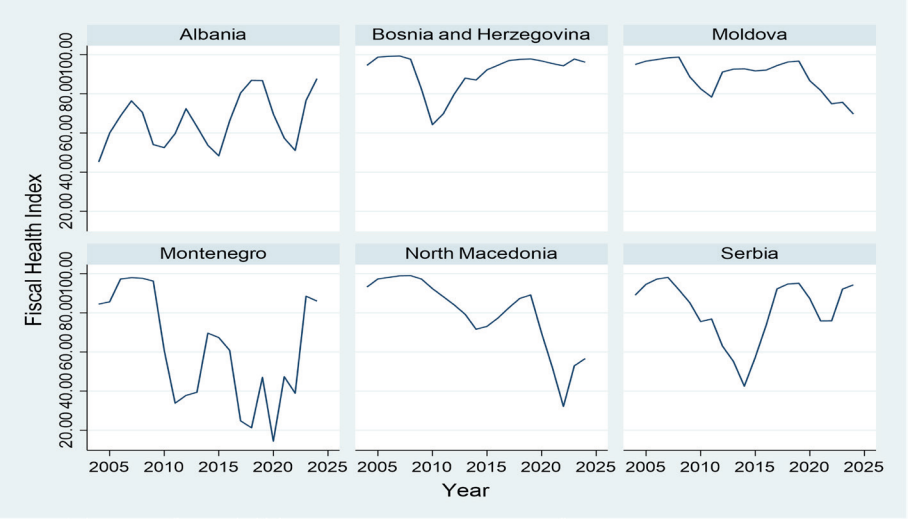
where x denotes public debt / average budget deficit, expressed as a percentage of GDP; α represents the threshold of debt / average budget deficit; β reflects the nonlinearity parameter, that is, the concavity of the public debt / average budget deficit score.

Following the methodology of Salamaliki and Venetis (2024), which is based on the values used in the assessment of the Heritage Economic Freedom Index, the nonlinearity parameter is set at β = 2. According to the same methodology, the threshold (α) is defined at 100% of GDP for public debt, while for the average budget deficit α is set at −7% of GDP. In the assessment of the public debt score, public debt-to-GDP ratios that are greater than or equal to 100% of GDP are assigned a score of zero. If the debt-to-GDP ratio is below α (i.e., below 100% of GDP), a concave penalization function is applied, whereby low debt-to-GDP ratios are penalized mildly, while the score deteriorates at an increasing rate as the debt-to-GDP ratio approaches the value of α. In the assessment of the average budget deficit score, balanced budgets or budget surpluses are assigned the maximum score of 100, whereas average deficits exceeding 7% of GDP receive a score of zero. For values of the average budget deficit as a percentage of GDP ranging from −7% to 0% of GDP, the same concave penalization function as in the debt score is applied, with the nonlinearity parameter set at β = 2.

In the analysis of fiscal resilience in CEFTA countries, the critical value, i.e., α = 100% of GDP for public debt, was set to reflect the findings of numerous studies that identify a zone of elevated fiscal risk around a public debt level of 100% of GDP for developed countries (Salamaliki and Venetis, 2024; Reinhart and Rogoff, 2010). At this level of indebtedness, the probability of losing investor confidence, the occurrence of fiscal stress, and the reduction of fiscal space significantly increase. In the CEFTA country analysis, the threshold for the average budget balance score was set at α = −7% of GDP, allowing the distinction between crisis-level fiscal imbalances and normal cyclical deficits. If the threshold were set lower, the indicator would overly penalize relatively common deficits and reduce the model's ability to highlight actual fiscal risks. The negative effects of public debt on fiscal sustainability become more pronounced as debt approaches higher levels, with marginal effects of growth being non-constant and accelerating (Reinhart and Rogoff, 2010). Accordingly, the nonlinearity parameter β = 2 implies that fiscal health does not decline linearly with increasing debt and deficits but deteriorates more rapidly as these approach the threshold, i.e., their critical value. Applying β = 2 prevents underestimation of fiscal risks in zones of high debt and chronic deficits, while

simultaneously avoiding extreme penalization that could result from higher values of β. In calculating the overall fiscal health score for CEFTA countries, the nonlinearity parameter β is set to 2 in order to increase sensitivity to large deviations from deficit and debt thresholds while still moderately responding to smaller deviations, thereby emphasizing high-risk fiscal positions without overly penalizing moderate imbalances. Trends in the Fiscal Health Index by country over the analysed period are presented in Figure 1.

Figure 1: Fiscal Health Index in CEFTA countries



Source: Authors

As a robustness check, we also employ an alternative Fiscal Health Index which, unlike the baseline specification, explicitly incorporates the conventional fiscal reference thresholds of a −3% budget balance and 60% public debt-to-GDP ratio.

The analysis of the Fiscal Health Index from 2004 to 2024 indicates differences in fiscal resilience and the dynamics of public finances among CEFTA countries. Although most CEFTA countries exhibit high initial values of the fiscal health index, the intensity of fiscal deterioration and the speed of recovery vary significantly. Bosnia and Herzegovina and Serbia maintained relatively stable fiscal health index values, while Montenegro and Albania experienced more pronounced fluctuations. North Macedonia and Moldova recorded more significant deteriorations in fiscal health in the later years of the observed period. During the global financial crisis and the economic crisis caused by the COVID-19 pandemic, Albania's fiscal health deteriorated, while periods of fiscal consolidation (2016-2019 and after 2022) resulted in its significant improvements. Although a temporary significant decline in the fiscal health index was recorded during the global financial crisis, Bosnia and Herzegovina's fiscal health remains relatively strong throughout the

observed period, including the COVID-19 pandemic. Montenegro stands out for its pronounced fiscal instability, with the lowest index values in 2017, 2018 and 2020, while in the last two years it recorded a strong recovery in fiscal health. After the deterioration of Serbia's fiscal position until 2014, the period after 2015 was characterized by successful fiscal consolidation, while the pandemic has a temporary negative effect on fiscal health. North Macedonia has been experiencing a long-term decline in fiscal health since 2009, which has intensified during the crisis caused by the COVID-19 pandemic, while a limited recovery in fiscal health has been evident in recent years. After 2019, when Moldova recorded a high value of the Fiscal Health Index, gradual and continuous deterioration of the fiscal position occurred, with no clear signs of full recovery by the end of the observed period.

The analysis of the Fiscal Health Index trends in CEFTA countries has shown that there are differences in the intensity of the impact of global economic crises on fiscal resilience. The global economic crisis of 2008 had pronounced negative effects on the fiscal health of Bosnia and Herzegovina and Moldova, whereas Montenegro, North Macedonia, and Albania demonstrated lower fiscal resilience during the crisis triggered by the COVID-19 pandemic.

Descriptive statistics presented in Table 2, show substantial heterogeneity across both fiscal and macroeconomic variables.

Table 2: Descriptive statistics of fiscal and macroeconomic variables

Stats	Mean	SD	Min	Max	N
gdebt	46.36	16.24	18.17	108.40	126
bbalance	-2.51	2.68	-11.01	8.43	126
fhealth	78.24	19.89	14.42	99.34	126
fhealth2	43.87	37.55	0	98.9	126
rgdp	3.17	3.78	-15.31	13.90	126
infl	4.38	4.60	-1.58	28.72	126
gov_con_finexp	17.92	3.85	10.39	29.94	126
trade_open	97.46	20.86	59.52	166.15	126
intra_cefta	9.79	7.25	0	29.65	118
mand_exp_share,	57.39	10.70	35.08	73.64	99
tax_rev_share	60.61	6.81	46.74	74.84	115
pdebt_service	2.99	2.53	0.62	13.03	124
interest_exp	1.48	0.81	0.44	3.85	126
gov_ef	-0.27	0.33	-1.08	0.33	119
pol_stab	-0.17	0.36	-1.16	0.82	118
corup_contol	-0.43	0.22	-1.04	-0.01	120

Source: Authors

Public debt averages around 46 percent of GDP across the six analysed CEFTA countries, but ranges widely from below 20 percent to over 108 percent, reflecting pronounced differences in fiscal positions across CEFTA countries and over time. The budget balance is negative on average, reflecting existence of persistent fiscal deficits in the last 20 years, while fiscal health index (fhealth) shows the relatively high average level, accompanied by significant variation across countries and over time, as indicated by its standard deviation. The alternative fiscal health indicator (fhealth2) reveals a lower average value and greater variability, reflecting a more conservative assessment of fiscal resilience, which is based on stricter fiscal reference thresholds for shares of budget balance and public debt in GDP. Real GDP growth is very volatile, including extreme values during crisis periods, while inflation is likewise volatile over the sample period. Government final consumption expenditure is comparatively stable, suggesting institutional rigidities on the expenditure side. Trade openness is generally high but varies across countries, reflecting different levels of integration into international trade, while the share of intra-CEFTA trade in GDP remains relatively modest on average, indicating that countries in the region are predominantly oriented toward EU markets and that the potential of the CEFTA agreement remains underutilized. When it comes to mandatory expenditure, this type of fiscal expenditure accounts for a substantial share of total government spending, indicating limited flexibility on the expenditure side of fiscal policy and constraining the scope for fiscal consolidation. At the same time, the share of mandatory expenditure varies considerably across countries, suggesting that fiscal authorities face different degrees of room for manoeuvre when pursuing expenditure-based consolidation. Tax revenue, measured as a share of total government revenue, is relatively stable, whereas public debt service exhibits marked variability, capturing periods of heightened fiscal stress. Interest expenditure, measured as a share of GDP, is relatively moderate on average but varies across countries and over time, reflecting differences in debt levels and borrowing costs. The WGI indicators (Government Effectiveness, Political Stability and Absence of Violence/Terrorism, and Control of Corruption) have negative average values and moderate variation across countries and over time, indicating relatively weak institutional quality and political stability in the region.

Before conducting panel unit root tests, whose results determine the choice of the appropriate estimator, it is essential to examine whether the panel data exhibit cross-sectional dependence. The presence of cross-sectional dependence has important implications for the selection of appropriate unit root tests. If the cross-sectional dependence exists, then first generation unit root tests are not appropriate. Given that the analysis focuses on six CEFTA countries over the period 2004-2024, cross-sectional dependence may arise due to common shocks, regional economic integration, trade linkages, or similar policy responses among the countries in the sample. To determine whether the time series across countries are cross-sectionally dependent, we apply the Pesaran (2007) cross-sectional dependence (CD) test, which is suitable for panels with relatively small cross-sectional dimensions and moderate time spans. If cross-sectional dependence is detected, second-generation panel unit root tests that explicitly account for such dependence

are employed in the subsequent analysis. The null hypothesis is cross-sectional independence, while rejection of the null indicates the presence of cross-sectional dependence.

The results of the Pesaran CD test are presented in the Table 3. The results show that the p-values of the test for all variables, except mandatory expenditure share political stability and absence of violence/terrorism, and control of corruption, are below 0.05. This implies rejection of the null hypothesis of cross-sectional independence and acceptance of the alternative hypothesis, indicating the presence of cross-sectional dependence among countries. In contrast, for mandatory expenditure share, the null hypothesis cannot be rejected, suggesting no cross-sectional dependence for this variable.

Table 3: Cross-sectional dependence test results (Pesaran CD Test)

Variable	CD statistic	p-value	Average corr.	Conclusion
gdebt	8.33	0.000	0.47	CD present
bbalance	8.12	0.000	0.46	CD present
fhealth	4.13	0.000	0.23	CD present
fhealth2	6.28	0.000	0.354	CD present
rgdp	13.26	0.000	0.75	CD present
infl	13.48	0.000	0.76	CD present
gov_con_finexp	3.39	0.001	0.19	CD present
trade_open	5.39	0.000	0.30	CD present
intra_cefta	3.38	0.001	0.190	CD present
mand_exp_share	0.04	0.965	-0.02	No CD
tax_rev_share	2.13	0.033	0.15	CD present
pdebt_service	4.85	0.000	0.34	CD present
interest_exp	2.02	0.044	0.114	CD present
gov_ef	4.99	0.000	0.289	CD present
pol_stab	1.52	0.128	0.083	No CD
corup_contol	0.37	0.713	0.021	No CD

Source: Authors

Considering detected cross sectional dependence, we proceed with the second-generation panel unit root test, and we employ Pesaran's 'A Simple Panel Unit Root Test in the Presence of Cross-Section Dependence' (Pesaran, 2007). This test is based on t-statistics from cross-sectionally augmented

Dickey–Fuller (CADF) regressions, which account for cross-sectional dependence and allow for heterogeneity across cross-sectional units. The panel test statistic is obtained by averaging the individual CADF t-statistics and is commonly referred to as the cross-sectionally augmented IPS (CIPS) statistic. This test is particularly suitable for our dataset because it explicitly accounts for cross-sectional dependence detected above, which is likely to arise in panels of countries exposed to common macroeconomic and fiscal shocks. The CIPS approach reduces this problem by extending individual ADF regressions with cross-sectional averages, which helps to control for unobserved common factors.

The results of the unit root tests are presented in Table 4. The tests are conducted using two alternative lag specifications (lag 0 and lag 1), including an intercept. The zero-lag specification captures the contemporaneous adjustment of the variables, while the inclusion of one lag allows for short-run dynamic effects and guards against serial correlation in the residuals. Given the relatively short time dimension of the panel, higher lag orders are avoided to preserve degrees of freedom. The consistency of results across both lag specifications also serves as a robustness check for the unit root test results and conclusion about the order of integration.

Table 4: Pesaran CIPS unit root test results

Variable	Lag	Test statistic	p-value	Order of intergation ††
gdebt	0	-1.311	0.872	I(1)
	1	-1.485	0.756	**I(1)**
bbalance	0	-2.009	0.265	I(1)
	1	-1.711	0.550	**I(1)**
fhealth	0	-1.006	0.972	I(1)
	1	-1.849	0.411	**I(1)**
fhealth2	0	-1.518	0.730	I(1)
	1	-1.562	0.691	**I(1)**
rgdp	0	-3.375***	0.000	I(0)
	1	-2.673**	0.011	**I(0)**
infl	0	-3.453***	0.000	I(0)
	1	-3.355***	0.000	**I(0)**
gov_con_finexp	0	-2.116	0.184	***I(1)***
	1	-2.777***	0.005	I(0)
mand_exp_share	0	0.629†	0.735	I(1)
	1	0.649†	0.742	**I(1)**

Variable	Lag	Test statistic	p-value	Order of intergation ††
tax_rev_share	0	-4.039***†	0.000	I(0)
	1	-4.018***†	0.000	**I(0)**
pdebt_service	0	-3.218***†	0.001	I(0)
	1	0.291†	0.614	I**(1)**
interest_exp	0	-2.137	0.171	I(1)
	1	-1.902	0.360	**I(1)**
trade_open	0	-0.875	0.987	I(1)
	1	-0.868	0.988	**I(1)**
intra_cefta	0	-0.513†	0.304	I(1)
	1	1.018†	0.846	**I(1)**
gov_ef	0	-2.127*†	0.017	I(0)
	1	0.666†	0.747	**I(1)**
pol_stab	0	-1.156†	0.124	I(1)
	1	-0.910†	0.181	**I(1)**
corup_contol	0	-0.767	0.989	I(1)
	1	-0.890	0.977	**I(1)**

*** p<0.01, ** p<0.05, * p<0.1
Notes: † indicates standardized Z[t-bar] statistics reported due to an unbalanced panel.
††I(0) and I(1) denote stationarity in levels and first differences, respectively.
Source: Authors

The results indicate a clear distinction between variables that are stationary in levels, I(0), and those that follow a unit root process. Key macroeconomic variables such as real GDP growth and inflation are found to be stationary, while fiscal indicators related to public debt, fiscal balance, expenditure structure and composite fiscal health measures are non-stationary in levels. These latter variables are highly persistent, indicating slow fiscal adjustment and policy inertia, a pattern that also characterizes the WGI indicators. Overall, the unit root evidence confirms a mixed order of integration across variables, justifying the use of an econometric model capable of accommodating both stationary and non-stationary regressors while accounting for cross-sectional dependence.

5 Results and discussion

This section presents the empirical results of the DCCE-ARDL estimations examining the short-run dynamics and long-run relationships between the fiscal health index and its macroeconomic and fiscal determinants. This will also demonstrate the fiscal resilience of CEFTA countries. Table 5 reports results from eight model specifications, starting from a baseline macroeconomic model

and gradually adding additional transmission channels: openness, growth, debt servicing, revenue capacity, inflation, and crisis effects. Across all model specifications, error-correction mechanism (ECM) adjustment coefficient is negative and statistically significant at the 1% level, indicating the existence of a stable long-run relationship between fiscal health and its determinants. The value of the ECM adjustment coefficient takes value approximately between −0.40 and −0.70, implying that about 40% to 70% of short-run deviations from the long-run equilibrium are corrected within one year. The results above demonstrate that CEFTA countries exhibited pronounced fiscal resilience during the analysed period. This interval suggests a moderate to relatively fast speed of adjustment, meaning that fiscal imbalances tend to disappear over time rather than persist. The stability of the ECM adjustment coefficient across all specifications of the estimated model provides further evidence of the dynamic stability of the estimated models and supports the use of the DCCE-ARDL framework for analysing fiscal health dynamics in heterogeneous panels. The coefficient on the lagged dependent variable (Fiscal health index (t-1)) is positive and highly statistically significant in all estimated models, with values generally lying between 0.30 and 0.60. This result points to a pronounced degree of fiscal persistence, reflecting the gradual nature of fiscal policy adjustment and institutional rigidities in budgetary processes. Taken together, these results indicate that fiscal health is characterized by strong short-run persistence combined with a stable long-run adjustment mechanism. While fiscal performance exhibits inertia and respond gradually to shocks in the short run, the negative and significant ECM adjustment coefficient ensures convergence toward the long-run equilibrium over time. This combination suggests that fiscal imbalances may persist temporarily, but they are not permanent and tend to be corrected in the medium run.

Table 5: DCCE-ARDL estimation results: Short-run dynamics and long-run relationships

VARIABLES	Model 1: Macro baseline	Model 2: Macro + Openness	Model 3: GDP channel	Model 4: Debt service	Model 5: Interest burden	Model 6: Revenue capacity	Model 7: Combined fiscal (debt service)	Model 8: Combined fiscal (interest burden)	Model 9: Inflation channel	Model 10: Crisis robustness
SHORT-RUN DYNAMICS										
Fiscal health index (t-1)	0.547***	0.492***	0.425***	0.438***	0.526***	0.392***	0.303***	0.340***	0.598***	0.499***
	(0.048)	(0.048)	(0.073)	(0.057)	(0.099)	(0.098)	(0.094)	(0.118)	(0.096)	(0.057)
Real GDP growth	1.228		1.450*							
	(1.068)		(0.817)							
Inflation	0.034	-0.383		0.243	0.567	-0.412	-0.017	0.458	-1.550***	-0.024
	(0.515)	(0.439)		(0.573)	(0.645)	(1.620)	(1.426)	(1.908)	(0.576)	(0.501)
Trade openness		0.251**							-0.005	
		(0.118)							(0.287)	
Public and publicly guaranteed debt service			-1.228	-2.726**			-0.908			-2.574**
			(1.400)	(1.159)			(1.02)			(1.175)
Interest expenditure					-17.619***			-12.031***		
					(5.996)			(3.354)		
Tax revenue share						1.743**	1.689***	1.473**		
						(0.692)	(0.578)	(0.684)		
General government final consumption expenditure									-0.912	
									(2.398)	
CRISIS DUMMIES										
d2008										-1.995
										(2.184)
d2020										-8.487**
										(4.212)
LONG-RUN RELATIONSHIPS										
ECM adj. coefficient	*-0.453***	*-0.508***	*-0.575***	*-0.562***	*-0.474***	*-0.608***	*-0.697***	-0.660***	*-0.402***	*-0.501***
	(0.048)	(0.048)	(0.073)	(0.057)	*(0.099)*	(0.098)	(0.094)	(0.118)	(0.096)	(0.057)
Real GDP growth	2.73		2.292*							
	(2.003)		(1.296)							
Inflation	-0.041	-0.667		0.171	0.800	-0.671	0.163	1.437	-5.411**	-0.239
	(1.142)	(0.861)		(0.927)	(1.335)	(2.273)	(1.696)	(3.054)	(2.265)	(0.884)
Trade openness		0.477**							-2.912	
		(0.228)							-3.276	
Public and publicly guaranteed debt service			-2.956	-4.691**			-1.158			-5.479**
			(2.595)	(2.273)			(1.629)			(2.613)
Interest expenditure					-35.727***			-21.325***		
					(8.550)			(7.014)		
Tax revenue share						3.100***	2.481***	2.472**		
						(1.002)	(0.739)	(1.139)		
General government final consumption expenditure									-35.162	
									(36.84)	
Observations	120	120	119	119	120	111	110	111	120	119
R-squared	0.514	0.669	0.544	0.657	0.474	0.613	0.665	0.606	0.55	0.598
Number of groups	6	6	6	6	6	6	6	6	6	6

*** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses.
Source: Authors

Regarding the short-run and long-run coefficients, the results indicate that fiscal variables play a more prominent role than basic macroeconomic variables in explaining fiscal health dynamics.

Real GDP growth has a positive but relatively weak impact on fiscal health, reaching only marginal levels of statistical significance in some specifications. Inflation is directly statistically significant only in Model 9 with negative effect. However, it may still play an indirect role in other specifications through its influence on nominal interest rates and, consequently, the cost of public debt. Debt service exhibits a negative and statistically significant effect on fiscal health in model specifications where inflation is included (Model 4 and Model 10) both in the short run and in the long run, while losing significance once revenue-side variables are introduced (Model 7). This pattern suggests that higher debt servicing costs (higher inflation is associated with higher nominal interest rates) can deteriorate fiscal health by increasing budgetary pressure. However, once revenue capacity is explicitly accounted for, as in specifications including the tax revenue share, the debt service variable loses statistical significance even when inflation is included. This indicates that the impact of debt service on fiscal health is not unconditional but depends on the broader fiscal structure. In this context, inflation dynamics may still influence the cost of public debt through nominal interest rates, but stronger revenue capacity appears to mitigate the adverse effects of debt servicing costs. This empirical regularity was consistently observed across alternative model specifications and highlights the importance of considering interactions between inflation, debt service, and revenue capacity when assessing fiscal health outcomes. Interest expenditure on public debt is also statistically significant and negative, implying that a higher share of interest payments in GDP reduces fiscal health. In contrast to the debt service variable, interest expenditure remains statistically significant even when revenue capacity is controlled for. This suggests that interest payments constitute a persistent fiscal burden that directly affects fiscal sustainability and cannot be fully offset by higher revenue capacity.

Trade openness also shows a positive and statistically significant effect on fiscal health in selected model specifications. This suggests that greater integration of CEFTA countries into international trade may support fiscal outcomes through higher economic activity, broader tax bases, and improved revenue performance. However, an additional variable capturing intra-CEFTA trade as a share of GDP was also considered in the empirical specification, but it did not appear statistically significant, which may be explained by the relatively modest share of intra-regional trade in the overall economic activity of CEFTA countries. On the revenue side, tax revenue share emerges as one of the most robust and stable determinants of fiscal health. The coefficient on tax revenue share is positive and statistically significant in both the short run and the long run across all specifications in which it is included (Model 6 - Model 8). This result indicates that stronger revenue collection capacity contributes to improved fiscal health by enhancing governments' ability to finance expenditures and service public debt in a sustainable way. Mandatory budget expenditure was not statistically significant in any specification, as well as the WGI indicators.

Overall, the results indicate that fiscal health is shaped by a combination of strong persistence and gradual long-run adjustment, reflecting the institutional nature of fiscal policies. Short-run fiscal outcomes exhibit inertia, while a stable adjustment mechanism ensures convergence toward a long-run equilibrium over time. The empirical evidence suggests that fiscal structure matters more than short-term macroeconomic conditions in explaining fiscal health dynamics.

To conclude, revenue-side capacity and interest payment expenditure emerge as the most robust and stable determinant of fiscal health, consistently improving fiscal outcomes and mitigating fiscal pressures. In contrast, debt servicing burden represent a key source of fiscal vulnerability, especially in environments characterized by inflationary pressures (and thus higher interest rates) and limited revenue capacity. Macroeconomic variables such as real GDP growth and inflation play a more conditional role, influencing fiscal health mainly through their interaction with fiscal channels rather than through direct effects. Taken together, these findings highlight that improving fiscal health requires not only favourable macroeconomic conditions but, more importantly, a sound fiscal framework based on strong revenue collection and prudent debt management, which allows governments to absorb shocks and correct fiscal imbalances over time.

In addition to the fiscal health index, the empirical analysis was extended by estimating the model using two additional indicators of fiscal resilience, namely general government gross debt (gdebt) and the budget balance (bbalance), expressed as a percent of GDP. The results based on these alternative dependent variables are reported in Appendix Table A1. When government debt is taken as the dependent variable. The results largely confirm the main mechanisms found in the baseline model (Table 5). Stronger real economic growth is associated with a statistically significant reduction in government debt, both in the short and long run, underscoring the role of robust economic performance contributes to debt sustainability. By contrast, interest payments exert a positive and significant effect on public debt across both specifications, which is expected considering that higher debt servicing costs contribute to debt accumulation. The error-correction term remains negative and statistically significant in all estimations, confirming the existence of a stable long-run relationship among variables used in the model. When the budget balance is used as the dependent variable, the results also remain broadly consistent with the previous findings. Real growth shows a positive and statistically significant effect on the budget balance, proving that stronger economic activity contributes to budget balance improvement. Interest payments have a negative, although statistically insignificant, relationship with the budget balance, suggesting that higher debt servicing costs may place pressure on fiscal balances. The error-correction term remains negative and statistically significant in all specifications, indicating convergence toward the long-run equilibrium. The significant lagged terms indicate persistence in both public debt and budget balance dynamics.

To additionally check the robustness of the baseline findings, the model was reestimated using an alternative fiscal health index (fhealth2) based on the conventional fiscal thresholds (−3% of GDP for the budget balance and 60%

of GDP for public debt - Maastricht criteria). The results, reported in Appendix Table A2, are broadly consistent with the baseline specification. The direction and statistical significance of the main explanatory variables remain largely unchanged across model specifications, with only minor differences. The lagged dependent variable remains statistically significant in almost all models, except in Model 8, while the tax revenue share loses statistical significance in Models 7 and 8. The debt service variable is not statistically significant across the specifications and the dummy for Global Economic Crisis 2008. The adjustment coefficients are similar in both index specifications, suggesting that the speed of adjustment toward the long-run equilibrium remains relatively stable even when alternative fiscal thresholds are used.

The obtained results are consistent with the findings of Krajišnik et al. (2021), who confirm that balanced public finances and a sustainable level of public debt are conditions for economic growth, as well as a solid premise for more effective coping with economic shocks, i.e., crisis periods within the cyclical movement of the economy. Furthermore, the results of the analysis for CEFTA countries align with the findings of Kurt et al. (2012), who, on a sample of 25 European countries, demonstrated that fiscal variables - primarily public revenues and expenditures - significantly affect fiscal health, or fiscal resilience, through their impact on the budget balance. Similar to the study by Compaoré et al. (2020), the analysis of fiscal resilience in CEFTA countries confirmed the importance of tax capacity in the context of strengthening fiscal resilience. Additionally, the conclusions reached by Yohou (2023) in the research on developing countries indicate that increasing tax revenues can expand fiscal space, i.e., the ability to finance the budget without raising debt, which ultimately contributes to strengthening fiscal health and fiscal resilience - a finding that is also supported by our analysis.

The fiscal resilience, or fiscal health, of CEFTA countries is significantly influenced by the level of debt and the burden of public debt servicing, which is also the conclusion of the analysis by Paraskevi and Salamaliki (2024), conducted on a sample of OECD countries. The results obtained in our analysis are consistent with studies indicating that the burden of public debt servicing represents one of the key sources of fiscal vulnerability. Empirical analysis by Ribliera (2023) shows that high public debt repayments substantially limit fiscal flexibility and reduce governments' capacity to respond to fiscal shocks, thereby increasing overall fiscal vulnerability.

Our results highlight that macroeconomic variables, such as real GDP growth and inflation, do not always act as direct determinants of fiscal health; rather, their effects depend on their interaction with fiscal channels. This observation is consistent with the findings of Afshan and Vien (2023), who also note that the economic foundation of fiscal health is primarily shaped by macro-fiscal interactions rather than pure macroeconomic effects, which aligns with our results.

6 Conclusions

The empirical analysis confirms that CEFTA member countries exhibited a moderate to high degree of fiscal resilience to external economic shocks during the observed period. The negative and statistically significant error correction term in all models indicates the existence of a stable long-term relationship between fiscal health and its determinants, implying that short-term fiscal imbalances are not persistent and that the system adjusts to disturbances within a relatively short period. The estimate that between 40% and 70% of short-term deviations are corrected within one year demonstrates the ability of CEFTA countries to respond quickly to temporary fiscal shocks.

The analysis of the lagged values of the Fiscal Health Index indicates pronounced fiscal persistence, meaning that fiscal policy responds gradually due to institutional and budgetary rigidities. This combination of inertia and long-term adjustment confirms institutional resilience to short-term shocks, including global crises, and suggests that CEFTA countries possess a functional mechanism for stabilizing fiscal health.

The results indicate that fiscal variables play a more significant role than basic macroeconomic indicators in explaining fiscal health. In particular, tax revenue and interest expenditure stand out as the most stable and important determinants of fiscal resilience, while debt servicing costs represent a source of vulnerability, especially during periods of inflation and high interest rates. However, a stronger revenue capacity mitigates the negative effects of debt servicing, further confirming that fiscal resilience depends on the internal fiscal structure.

Short-term macroeconomic variables, such as GDP growth and inflation, have a limited and conditional impact on fiscal health, primarily operating indirectly through fiscal channels. The results indicate that external shocks, such as the 2008 financial crisis and the COVID-19 pandemic, have predominantly short-term negative effects on fiscal health, while in the medium term, these effects are adjusted through institutional management of fiscal revenues and public debt, without compromising the long-term fiscal resilience of CEFTA countries.

Overall, the results confirm the research objective of the study and the proposed research hypothesis, which states: fiscal health allows for the assessment of the level of fiscal resilience and the identification of factors that contribute to greater or lesser vulnerability of CEFTA countries to external shocks. It is concluded that improving fiscal health primarily requires a strong revenue capacity, balanced public finances, and responsible management of public debt, which enables the absorption of temporary shocks and ensures long-term fiscal stability.

The key contribution of this study lies in identifying revenue capacity and interest burden as the most robust determinants of fiscal resilience in CEFTA countries. Although the results provide relevant insights into the fiscal resilience of CEFTA countries, the analysis is subject to certain limitations, including a relatively small country sample, a limited time dimension due to data availability, and reliance on a single composite fiscal health indicator,

while future research could extend the analysis to a broader set of countries, longer time periods, and alternative measures of fiscal resilience.

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Appendix

Table A1: DCCE-ARDL Results: Governement Debt and Budget Balance

VARIABLES	Dependent variable: General government gross debt			Dependent variable: Budget balance		
	Model A1: Baseline	Model A2: Interest burden	Model A3: Fiscal structure	Model A4: Baseline	Model A5: Interest burden	Model A6: Fiscal structure
SHORT-RUN DYNAMICS						
Lagged dependent variable (t−1)	0.683***	0.331**	0.200	0.305***	0.214***	0.148***
	(0.061)	(0.139)	(0.149)	(0.076)	(0.030)	(0.045)
Real GDP growth	-1.080***			0.271**		
	(0.217)			(0.114)		
Inflation	-0.451	-0.299	0.329	0.133	0.206	0.096
	(0.339)	(0.473)	(0.435)	(0.242)	(0.229)	(0.260)
Interest payments		13.231***	15.737**		-2.604	-1.796
		(2.951)	(7.173)		(1.731)	(1.119)
Tax revenue share			-0.399			0.144
			(0.728)			(0.126)
LONG-RUN RELATIONSHIPS						
ECM adjustment coefficient	*-0.317****	*-0.669****	*-0.800****	*-0.695****	*-0.786****	*-0.852****
	(0.061)	*(0.139)*	*(0.149)*	*(0.076)*	*(0.030)*	*(0.045)*
Real GDP growth	-4.594***			0.373**		
	(1.444)			(0.148)		
Inflation	-1.418*	-2.844	0.857	0.223	0.290	0.171
	(0.797)	(2.414)	(0.865)	(0.423)	(0.323)	(0.360)
Interest payments		35.587*	33.288		-3.038	-1.773
		(19.627)	(23.441)		(1.947)	(2.300)
Tax revenue share			-1.492			0.141
			(1.922)			(0.143)
Observations	120	120	111	120	120	111
R-squared	0.310	0.358	0.257	0.694	0.760	0.611
Number of groups	6	6	6	6	6	6

*** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses.
Source: Authors

Table A2: Robustness check – alternative fiscal health index (fhealth2)

VARIABLES	Model 1: Macro baseline	Model 2: Macro + Openness	Model 3: GDP channel	Model 4: Debt service	Model 5: Interest burden	Model 6: Revenue capacity	Model 7: Combined fiscal (debt service)	Model 8: Combined fiscal (interest burden)	Model 9: Inflation channel	Model 10: Crisis robustness
SHORT-RUN DYNAMICS										
Fiscal health index (t-1)	0.433***	0.423***	0.290***	0.284***	0.330***	0.239***	0.194**	0.061	0.315***	0.424***
	(0.113)	(0.092)	(0.093)	(0.059)	(0.069)	(0.083)	(0.084)	(0.090)	(0.115)	(0.108)
Real GDP growth	3.012**		2.160*							
	(1.338)		(1.186)							
Inflation	0.987	-0.305		1.586	1.406	0.626	2.407	1.697	-1.379	1.197
	(2.376)	(1.829)		(2.085)	(2.366)	(3.910)	(3.194)	(3.997)	(1.709)	(2.083)
Trade openness		1.084***							0.910	
		(0.396)							(0.617)	
Public and publicly guaranteed debt service			-0.780	-3.077			2.050			-2.328
			(5.566)	(4.270)			(3.343)			(3.693)
Interest expenditure					-29.604***			-20.839***		
					(5.985)			(7.237)		
Tax revenue share						2.819*	1.904	2.082		
						(1.629)	(1.404)	(1.955)		
General government final consumption expenditure									-0.510	
									(4.207)	
CRISIS DUMMIES										
d2008										-2.598
										(7.068)
d2020										-15.562
										(13.541)
LONG-RUN RELATIONSHIPS										
ECM adjustment coefficient	-0.567***	-0.577***	-0.710***	-0.716***	-0.670***	-0.761***	-0.806***	-0.939***	-0.685***	-0.576***
	(0.113)	(0.092)	(0.093)	(0.059)	(0.069)	(0.083)	(0.084)	(0.090)	(0.115)	(0.108)
Real GDP growth	5.620**		2.887**							
	(2.534)		(1.428)							
Inflation	0.842	-2.411		1.321	2.134	-0.655	2.206	1.451	-3.661	2.141
	(4.828)	(3.796)		(2.943)	(3.251)	(5.418)	(4.075)	(5.129)	(2.528)	(6.275)
Trade openness		1.823*							1.214	
		(0.920)							(0.979)	
Public debt service			-2.653	-4.554			2.716			-5.175
			(7.454)	(5.444)			(4.132)			(5.616)
Interest expenditure					-50.350***			-23.204**		
					(14.407)			(9.318)		
Tax revenue						4.177*	2.804*	3.087		
						(2.251)	(1.554)	(2.738)		
Government consumption									-2.086	
									(6.071)	
Observations	120	120	119	119	120	111	110	111	120	119
R-squared	0.487	0.568	0.571	0.613	0.520	0.641	0.580	0.500	0.411	0.474
Number of groups	6	6	6	6	6	6	6	6	6	6

*** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses.
Source: Authors

Sustainability Reporting and Financial Performance: Empirical Evidence from the Republic of Serbia

Original scientific paper

Jelena J. Stanković[1], Bojana Novićević Čečević[2], Marina Stanojević[3], Ivana Marjanović[4]

ABSTRACT

This study examines whether sustainability reporting is associated with differences in corporate financial performance in the Republic of Serbia. Using a sample of 100 top-performing companies and covering the period 2022–2024, the analysis compares entities that publish sustainability reports with those that provide only limited sustainability-related disclosures within management reporting and those that do not disclose such information. Financial performance is captured through three indicators: return on assets (ROA), liquidity, and indebtedness. Given the characteristics of the dataset, non-parametric procedures are applied, including the Kruskal–Wallis test and pairwise Mann–Whitney comparisons, to identify statistically significant differences across reporting groups. The results suggest that, within the observed Serbian business context, the presence of sustainability reporting is not a decisive factor in explaining variations in ROA, liquidity, or leverage across companies. By differentiating between stand-alone sustainability reports, sustainability disclosures within management reports, and the absence of such disclosures, the study offers a more nuanced perspective on reporting practices in a transition economy. The findings contribute to the emerging evidence on sustainability disclosure in transition economies and offer practical implications for managers and policymakers aiming to strengthen reporting practices and align them with evolving regulatory and stakeholder expectations.

1 *Full professor, University of Niš, Faculty of Economics, Niš, Serbia; E-mail: sjellenna@gmail.com*

2 *Associate professor, University of Niš, Faculty of Economics, Niš, Serbia; E-mail: bojana.novicevic@eknfak.ni.ac.rs*

3 *Associate, University of Niš, Faculty of Economics, Niš, Serbia; E-mail: marina.stanojevic@eknfak.ni.ac.rs*

4 *Teaching assistant, University of Niš, Faculty of Economics, Niš, Serbia; E-mail: ivana.veselinovic@eknfak.ni.ac.rs*

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1 Introduction

In today's business environment, sustainable business is becoming an increasingly important factor for the long-term success and competitiveness of companies. Global trends, such as growing pressure from investors, regulations, and social expectations, encourage companies to adopt sustainable practices and report transparently on their operations. In this context, sustainability reporting has become a key element in the communication with stakeholders, including investors, regulators, and the broader public. Although it is often used as a tool to demonstrate corporate social responsibility, the question remains whether this practice has a concrete impact on the financial success and the performance of companies.

The Republic of Serbia, like many other countries, faces challenges in implementing sustainable business practices. Although it is not a member of the European Union, Serbia must align its legislation with international standards and meet obligations under the 2030 Agenda for Sustainable Development. In that sense, legislative frameworks in Serbia stimulate socially responsible business; however, the number of companies that actively publish sustainability reports still varies.

The aim of this research is to examine whether there are significant differences in financial performance between companies that publish sustainability reports and those that do not. The research sample includes 100 companies from the list of the most successful business entities in Serbia, according to data from the Business Registers Agency, and the analysed period covers 2022–2024. To achieve the research objective, statistical methods were applied, predominantly non-parametric techniques, whereby differences in basic balance-sheet positions (such as total assets, revenues, and net profit) were analysed first, followed by key financial performance indicators such as return on assets (ROA), liquidity, and indebtedness.

The research results indicate that sustainability reporting is not a statistically significant factor affecting the financial performance of companies in the Republic of Serbia. Although there are differences in balance-sheet positions among companies that report on sustainability, these differences are not sufficient to conclude that the practice of sustainability reporting directly affects financial performance.

The contribution of this paper is reflected in both its contextual and methodological focus. Contextually, the paper provides empirical evidence from Serbia, as a transition economy, in which sustainability reporting is developing under conditions of partial regulatory harmonization, uneven reporting maturity, and heterogeneous company practices. Methodologically, the study goes beyond a simple dichotomous distinction between reporting

and non-reporting companies by differentiating among those that publish a stand-alone sustainability report, those that disclose sustainability-related information within the management report, and those that do not publish sustainability-related information at all. Such an approach enables a more nuanced empirical assessment of whether different forms of sustainability disclosure correspond to differences in financial position and performance. In that sense, the paper contributes to the still limited empirical literature on sustainability reporting and financial outcomes in transition economies.

Starting from the defined problem, after the introduction the authors provide an overview of the existing literature on the examined issue and previous research results. Then, the methodology and the results obtained, as well as their discussion, are presented. At the end of the paper, the conclusions of the conducted research are presented.

2 Theoretical background

In the contemporary business environment, sustainable business and sustainability reporting have become key factors for the long-term success of companies. At the global level, increasing pressure from investors, regulators, and society encourages companies to integrate sustainability into their business strategies and report transparently on its aspects, which significantly increases the need for structured and credible mechanisms for presenting non-financial performance. Although the importance of sustainability reporting is undeniably increasing, the question of its impact on the financial performance of companies continues to attract considerable attention among researchers, both due to different methodological approaches and due to the heterogeneity of market and institutional frameworks in which companies operate. Sustainability reporting is a vital instrument for companies that wish to demonstrate their social and environmental initiatives and improve transparency towards investors, regulators, and the broader public, thereby building trust and legitimacy among all stakeholder groups. According to Elkington (1997), the triple bottom line (TBL) concept comprises three key aspects of sustainability: economic, social, and environmental responsibility, and this model has significantly contributed to the development of more comprehensive corporate sustainability strategies that go beyond purely profit-driven logic. In this sense, Freeman (1984) emphasizes the importance of involving all relevant stakeholders in business decision-making, thereby giving sustainability a broader strategic context. In addition, Carroll (1999) highlights a hierarchy of corporate social responsibility, including economic, legal, ethical, and philanthropic dimensions, which contributes to understanding sustainability as a multi-layered concept. Increased regulation and market dynamics have led to the adoption of mandatory sustainability reporting guidelines in many countries, including the legislative frameworks of the European Union, which impose an obligation for large corporations to disclose non-financial information. Although Serbia, as a candidate country for membership in the European Union, is aligning its legislation with EU standards, sustainability reporting is still not mandatory for all organizations, and the implementation of these guidelines varies among companies, leading to differences in the degree of compliance and the quality of reports (Belić

& Draškić, 2020). In Serbia, there is significant variation in the application of sustainability reporting—some companies decide to report on sustainability as a separate document, while others integrate this topic into their standard business reports (Marković & Petrović, 2019), and the choice of approach often depends on the type of activity, the size of the company, and stakeholder requirements (Jovanović & Simić, 2018). Different authors point out that the existence of sustainability reporting does not necessarily imply a high level of sustainable practice, because the qualitative component of reports varies and often depends on available resources and expertise in sustainable management (Dahlsrud, 2008). The relationship between sustainability reporting and the financial performance of companies is the subject of numerous empirical studies, and the results are often ambiguous. Many studies indicate a positive correlation between sustainable business practices and better financial results. For example, Eccles et al. (2014) claim that companies that implement sustainable practices and report on them enjoy a better reputation, have easier access to capital, and lower business risk. McWilliams and Siegel (2000) suggest that transparency and corporate social responsibility can increase competitiveness and efficiency, while Kotsantonis and Serafeim (2019) confirm that high-quality reporting increases investor confidence and reduces the cost of capital. However, Cochran and Wood (1984) point out that these effects are often indirect and are manifested only in the long term, while some authors (O'Dwyer, 2003; Jovanović & Simić, 2018) emphasize that the absence of reporting can be an indicator of poor corporate governance. Sullivan and Mackenzie (2017), as well as Martínez-Ferrero and Frias-Aceituno (2015), note that companies with better financial performance more often have the resources to invest in sustainability, which creates a positive feedback loop. In the context of developing markets such as Serbia, Brammer and Millington (2008) highlight the importance of adapting sustainability practices to local institutional frameworks and capacities, while Giorgi and Haider (2018) point to implementation challenges due to limited resources, regulatory instability, and lack of expertise. Cheng, Ioannou, and Serafeim (2014) further emphasize that in such environments there is often uneven implementation of sustainability practices, which makes comparative analyses and drawing precise conclusions more difficult. Methodologically, most research uses quantitative approaches, including analysis of variance (ANOVA), regression models, and non-parametric tests to determine the statistical significance of the relationship between sustainability and performance. Kolk (2003) uses the Kruskal–Wallis test to compare income statement indicators in companies that report on sustainability and those that do not, while Nguyen and Nguyen (2020) highlight the importance of reliable statistical modelling in assessing the effectiveness of sustainable business models. In the domestic literature, although sustainability reporting is becoming an increasingly important factor for company competitiveness, there is still a significant gap in the research corpus. Jovanović and Simić (2018) state that empirical research in Serbia is still in its infancy and that there is a need for deeper analyses that would take into account the specifics of the local market, the degree of regulatory development, and the real capacities of domestic companies to implement sustainability practices. In this context, it is necessary to conduct additional research that would include a broader sample of companies, in order to draw more reliable conclusions about the

real impact of sustainability reporting on financial performance in the Serbian business context.

Although the existing literature provides important insights into the relationship between sustainability reporting and financial performance, several gaps remain. First, much of the empirical evidence originates from developed institutional environments, where reporting practices are more standardized, investor expectations more pronounced, and regulatory systems more mature. As a result, the conclusions of such studies cannot be transferred without reservation to transition economies, where sustainability reporting is often characterized by uneven implementation, lower comparability, and substantial differences in reporting quality. Second, in the domestic and broader regional literature, empirical studies remain relatively scarce and are more frequently oriented towards descriptive analyses of reporting practices than towards testing whether different forms of sustainability disclosures are associated with measurable financial outcomes. Third, previous studies often rely on a binary distinction between companies that report and those that do not, which may obscure important differences between stand-alone sustainability reporting and limited sustainability disclosure within mandatory business reports. In this sense, the present study seeks to address the identified research gap by empirically examining the Serbian context through a more differentiated classification of reporting practices and by assessing whether such differences are reflected in both balance-sheet positions and selected financial performance indicators.

3 Methodology of empirical research

The aim of the research is to examine whether there are statistically significant differences in financial positions and calculated performance measures between companies that prepare sustainability reports, companies that publish non-financial performance in the management report, and companies that do not address the sustainability issue at all.

The research sample consists of companies with highest revenues achieved in 2022. The authors limited the analysis period to three years, this is, 2022–2024. The data were collected from publicly available financial statements of companies from the list on the website of the Business Registers Agency and from other websites dealing with credit rating assessments. The initial sample of 100 companies was adjusted by excluding two entities for which financial statements were not available for all observed years. Thus, the final sample includes 98 companies, with 292 observations. Table 1 presents the structure of the observed sample by company type, territorial affiliation, and business sector.

Table 1: Sample characteristics

Variables	Frequency	Valid %
Type of company		
LLC (DOO)	80	81.6%
Public enterprise (JP)	5	5.01%
Joint-stock company (AD)	13	13.39%
Region		
Belgrade	56	57.14%
Vojvodina	21	21.42%
Central and Western Serbia	14	14.28%
Southern and Eastern Serbia	7	7.14%
Sector		
Information and communication	4	4.0%
Wholesale and retail trade	34	34.7%
Transport	7	7.1%
Manufacturing	34	34.7%
Construction	8	8.2%
Electricity supply	7	7.1%
Mining	3	3.1%
Arts and entertainment	1	1.0%

Source: Authors

Of the total number of companies in the observed sample, 94 are large, while 4 are medium-sized. The ownership structure analysis clearly shows that the largest number of companies are registered as limited liability companies, 80 (81.6%). There are 13 joint-stock companies (13.39%) and 5 public enterprises (5.01%).

Regarding regional affiliation, 56 companies belong to the Belgrade region, accounting for 57.14%. The Vojvodina region includes 21 companies. A total of 7 companies operate in Southern and Eastern Serbia (Southern Serbia 4, Eastern Serbia 3), while 14 companies are located in Central and Western Serbia, seven from each part of the country.

The analysis of the sample from the perspective of the region in which the company has its headquarters indicates that the highest number of them are from the Belgrade region, 55 (55.6%). Twenty-two companies from the sample are headquartered in Vojvodina (22.2%), eight in Central Serbia (8%) and seven in Western Serbia (7%). The smallest number of companies have

their headquarters in Southern Serbia (four) and Eastern Serbia (three).

The largest number of companies in the sample operate in manufacturing and in wholesale and retail trade, 34 (34.7%) in each activity. Eight companies operate in construction, while 7 provide services in transport and electricity supply. The information and communication sector includes 4 companies, mining includes 3, and the arts sector includes 1.

By analysing the available data, the authors found that, despite the existence of a legal obligation for sustainability reporting, companies operating in the Republic of Serbia do not fully meet these requirements. For the observed sample, the situation regarding the treatment of sustainability is shown in the following table:

Table 2: Overview of companies by treatment of sustainability

Variables	Frequency	Valid %
Publish a Sustainability Report (SR)	54	55.1%
Publish some data in the Management Report	14	14.3%
Do not publish sustainability-related data (No report)	30	30.6%
Total	98	100%

Source: Authors

Of the total of 98 companies, 54 prepare a Sustainability Report. Most of these companies belong to a group, so their sustainability reports are part of the group report, but there are also companies that are not part of a group and nevertheless publish a sustainability report. Fourteen companies present certain aspects of sustainability in the management report available on the website of the Business Registers Agency. For 30 companies with highest revenues in the Republic of Serbia, despite numerous attempts and additional efforts, the authors were unable to find a sustainability report or any sustainability-related information associated with these companies.

The collected data were analysed in the statistical package for the social sciences IBM SPSS Statistics 21.0 (Statistical Package for the Social Sciences – SPSS, Version 21.0). The observed financial performance measures include return on assets (ROA), liquidity, and indebtedness, while the sustainability disclosure category serves as the grouping variable in the comparative analysis.

A specific methodological feature of this study lies in the operationalization of sustainability disclosure through three empirically observable categories of companies. This approach was considered particularly appropriate for the Serbian business context, in which sustainability-related disclosure appears in different forms and levels of formalization. By distinguishing between stand-alone sustainability reports, sustainability information disclosed within management reports, and the absence of sustainability-related disclosure, the analysis captures not only whether companies report, but also how they report.

This distinction is important because, in transition economies, the format of disclosure may reflect different levels of institutional pressure, organizational maturity, and strategic commitment to sustainability. Given the characteristics of the dataset and the absence of normal distribution, non-parametric procedures were selected as the most appropriate analytical framework for identifying statistically significant differences among the observed groups.

4 Research results and analysis

The empirical research presented below aims to determine whether there are statistically significant differences in original financial positions and calculated performance measures among three groups of companies that treat the sustainability issue differently. To test the defined hypotheses, a univariate one-way analysis of variance (ANOVA) was applied. However, due to the lack of normality in the distribution of the selected variables, the Kruskal–Wallis test was applied as an appropriate non-parametric substitute.

4.1 Testing differences between three categories of companies in terms of original financial positions

Among the original financial positions, the authors decided to test differences in the following items: total assets, total revenues, and net profit. These balance-sheet items are most often used for compiling lists of the most successful companies, so we considered them relevant for this research. Before examining differences for each original financial position by year, we tested the significance of differences among these three groups for the entire observed period. The results of the Kruskal–Wallis test are presented in the following table:

Table 3: Results of difference testing for the entire observation period

	Assets	**Total revenue**	**Net profit**
Chi-Square	15.127	10.330	11.824
df	2	2	2
Asymp. Sig.	.001	.006	.003

a. Kruskal–Wallis Test; b. Grouping Variable: report
Source: Authors

The results of the previous analysis indicate that there is a difference between companies that publish a sustainability report, companies that present sustainability information in the management report, and companies that do not address sustainability, at the significance level $p = 0.001$ ($\chi^2 = 15.127$). Based on rank data obtained during processing in the statistical program, companies that publish a sustainability report as a separate document have the highest asset value (Mean Rank = 162.52). Lower asset ranks are recorded for companies that present sustainability data in the management report (150.33), while the lowest asset amount is observed for companies that

do not publish any sustainability data (119.13).

Regarding total revenue, the results also indicate statistically significant differences between categories of companies (χ^2 = 10.330, p = 0.006). The rank order is the same as for assets: companies that publish a sustainability report, 160.72; companies that present sustainability data in the management report, 145.02; and companies that do not publish a sustainability report, 124.87.

The Kruskal–Wallis test results shown in Table 3 also indicate that companies in the sample differ by net profit (χ^2 = 11.824, p = 0.003). The rank order is the same as in the previous two cases: 162.35, 139.10, and 124.70.

Given that we determined differences in original financial positions, at the next level of analysis we sought to identify which groups differ from each other. For these purposes and taking into account the absence of normality in the distribution of the selected variables, we conducted a non-parametric alternative - the Mann–Whitney U test.

Table 4: Mann–Whitney U test results for differences in the size of total assets

Comparison	N (Group 1)	Mean Rank (Group 1)	N (Group 2)	Mean Rank (Group 2)	U / Z / Sig.
SR vs Management Report	162	104.41	42	95.12	U=3092.00; Z=-0.909; Sig=0.363
SR vs No report	162	139.61	90	102.90	U=5166; Z=-3.831; Sig=0.000
Management Report vs No report	42	76.71	90	61.73	U=1461; Z=-2.096; Sig=0.036

Source: Authors

Based on the Mann–Whitney U test results shown in Table 4, we can conclude that differences in total assets exist between companies that publish a sustainability report as a separate document and companies that do not publish this report (p = 0.000), and between companies that present sustainability information in the management report and those that do not (p = 0.036). There is no difference in total assets between companies that address sustainability either through a sustainability report or through the management report. Moreover, based on average ranks we can conclude that companies with higher asset amounts address sustainability in some way.

At the next level of analysis, we examined which company categories show statistically significant differences in total revenues.

Table 5: Mann–Whitney U test results for differences in total revenues

Comparison	N (Group 1)	Mean Rank (Group 1)	N (Group 2)	Mean Rank (Group 2)	U / Z / Sig.
SR vs Management Report	162	104.75	42	93.83	U=3038; Z=-1.068; Sig=0.286
SR vs No report	162	137.47	90	106.76	U=5513; Z=-3.205; Sig=0.001
Management Report vs No report	42	71.10	90	64.36	U=1630; Z=-1.270; Sig=0.040

Source: Authors

Based on the results shown in Table 5, we see that there are no differences in revenues between companies that publish a sustainability report and those that publish sustainability data within the management report ($p = 0.363$). Differences in revenues exist between companies that publish a sustainability report as a separate document and companies that do not publish this report ($p = 0.000$), and between companies that present sustainability information in the management report and those that do not ($p = 0.040$).

In the final stage of this part of the analysis, we assessed whether the company categories differ in net profit.

Table 6: Mann–Whitney U test results for differences in the level of net profit achieved

Comparison	N (Group 1)	Mean Rank (Group 1)	N (Group 2)	Mean Rank (Group 2)	U / Z / Sig.
SR vs Management Report	162	105.87	42	93.83	U=2856; Z=-1.601; Sig=0.109
SR vs No report	162	137.98	90	105.84	U=5431; Z=-3.353; Sig=0.001
Management Report vs No report	42	71.10	90	64.36	U=1697; Z=-0.943; Sig=0.346

Source: Authors

Companies that do not publish a sustainability report show statistically significant differences from companies that publish the report as a separate

document (p = 0.001). Between the other groups there are no differences in net profit.

4.2 Testing differences between three categories of companies in terms of calculated performance

Based on the reviewed literature and the most commonly applied indicators in practice, the authors decided to examine the statistical significance of differences in the following performance measures: return on assets (ROA), liquidity, and indebtedness. First, we examined whether there were differences in these performance measures during the observed three-year period. The results are presented in the following table.

Table 7: Results of difference testing for the entire observation period

	ROA	Liquidity	Indebtedness
Chi-Square	2.894	5.031	.791
df	2	2	2
Asymp. Sig.	.235	.041	.673

a. Kruskal–Wallis Test; b. Grouping Variable: report
Source: Authors

The Kruskal–Wallis test results showed that there are no statistically significant differences between the formed groups with respect to ROA. Also, there are no differences regarding company indebtedness. Statistically significant differences between the three groups of companies were found for the liquidity indicator. To determine which companies differ from one another, we performed the Mann–Whitney U test.

Table 8: Mann–Whitney U test results for differences in company liquidity

Comparison	N (Group 1)	Mean Rank (Group 1)	N (Group 2)	Mean Rank (Group 2)	U / Z / Sig.
SR vs Management Report	162	97.76	42	120.90	U=2629; Z=-2.268; Sig=0.023
SR vs No report	162	126.82	90	125.92	U=7238; Z=-0.094; Sig=0.925
Management Report vs No report	42	75.33	90	62.38	U=1519; Z=-1.813; Sig=0.070

Source: Authors

Based on the research results shown in Table 8, we can observe that differences in liquidity exist between companies that publish a sustainability report as a separate document and companies that publish sustainability data in the management report ($p = 0.023$). When comparing the other groups, no statistically significant differences were found.

5 Discussion

The results obtained in this study should be interpreted in the broader context of the international literature on sustainability reporting and financial performance, as well as in relation to the specific features of the Serbian institutional environment. A substantial part of the international empirical literature suggests that companies engaged in sustainability reporting may achieve better financial outcomes through enhanced reputation, greater stakeholder trust, lower information asymmetry, and improved access to capital. At the same time, other studies emphasize that the relationship between sustainability disclosure and financial performance is neither uniform nor immediate, but rather depends on reporting quality, the strategic integration of sustainability into business operations, industry characteristics, time horizon, and the broader institutional setting. In that sense, the findings of this study are more closely aligned with those strands of the literature which argue that the mere existence of sustainability disclosure does not automatically produce measurable improvements in financial performance.

A particularly important finding of this research is that statistically significant differences were found in original financial positions, especially in total assets, total revenues, and partially in net profit, whereas the differences in relative financial performance indicators were much more limited. This pattern suggests that larger and economically stronger companies are more likely to disclose sustainability-related information in some form, which is consistent with the argument that companies with greater organizational capacity, public visibility, and stakeholder exposure are more inclined to formalize sustainability-related reporting. However, the fact that such companies do not simultaneously exhibit statistically significantly better ROA or lower indebtedness indicates that sustainability reporting itself should not be interpreted as a direct determinant of superior short-term financial efficiency. Rather, it may function more as an instrument of legitimacy, transparency, and strategic communication than as an immediate driver of accounting-based performance.

The absence of statistically significant differences in ROA and indebtedness may be explained by several features of the Serbian context. First, Serbia is a transition economy in which sustainability reporting practices are still evolving under conditions of partial regulatory harmonization and uneven institutional maturity. In such an environment, the preparation of a sustainability report may reflect formal compliance, parent-company requirements, or reputational signalling, rather than a deeply embedded sustainability strategy capable of generating direct financial effects. Second, the quality, consistency, and comparability of sustainability-related disclosures remain uneven. Since some companies publish stand-alone reports while others disclose only selected sustainability information in management reports, the informational value of

such disclosures may differ substantially. Third, external market mechanisms that often strengthen the financial effects of sustainability reporting in more developed economies—such as stronger investor scrutiny, broader ESG-based capital allocation, and more developed assurance practices—are likely to be less pronounced in Serbia. Consequently, the financial benefits of sustainability disclosure may remain weak, indirect, or delayed.

When compared with international empirical evidence, the Serbian findings therefore point to the importance of contextualizing the relationship between sustainability reporting and financial performance. In developed markets, positive effects are more often associated with higher-quality, externally validated, and strategically embedded sustainability reporting. In the Serbian setting, however, the existence of disclosure alone appears insufficient to generate statistically robust differences in relative financial performance. This does not diminish the relevance of sustainability reporting; rather, it suggests that its effects are mediated by institutional maturity, reporting quality, stakeholder awareness, and the degree to which sustainability is integrated into the company's broader strategic and operational framework.

6 Conclusions

In recent years, companies have increasingly focused on the aspect of sustainable business. In order to inform the public about their efforts to protect the environment, companies are obliged to prepare a sustainability report. However, despite the existence of a legal obligation, in the Republic of Serbia there are companies that do not do so. The authors found that some companies prepare a sustainability report as a separate document, others publish sustainability data within the management report, while some companies do not publish this information at all. The authors' idea was to examine whether there are differences in balance-sheet positions and performance among these three groups of companies. The list of the most successful companies by total revenues served as the basis for data collection. The final sample included 98 companies.

The authors first examined whether there are differences in balance-sheet positions such as assets, revenues, and net profit. The results showed that there are differences in the amounts of these positions among the stated categories of companies. Thus, differences in total assets were observed between companies that publish a sustainability report as a separate document and those that do not publish such a report, as well as between companies that include sustainability information in the management report and those that do not. A similar pattern was observed for revenues—differences exist between companies that publish a sustainability report as a separate document and those that do not, as well as between companies that publish sustainability within the management report and those that omit it. Regarding net profit, companies that do not publish a sustainability report differ statistically significantly from those that publish that report as a separate document. Based on this, it can be concluded that there are differences in balance-sheet positions between companies that take sustainability into account and those that do not.

When it comes to performance measures, the authors decided to test differences in ROA, liquidity, and indebtedness indicators. The results showed that only liquidity exhibits statistically significant differences among groups of companies. That difference was identified between companies that publish a sustainability report as a separate document and those that include sustainability data in the management report.

The findings also carry several practical implications. For managers, the results suggest that sustainability reporting should not be approached merely as a formal obligation or a reputational instrument, but rather as part of a broader strategic process involving governance improvement, stakeholder communication, risk management, and long-term value creation. The potential business benefits of sustainability reporting are likely to depend less on the mere existence of disclosure and more on its credibility, consistency, comparability, and integration into business decision-making. For policymakers and regulators, the findings underline the importance of further strengthening the institutional framework for sustainability reporting in Serbia through clearer reporting guidance, stronger alignment with evolving European standards, and support for companies in improving the quality and usefulness of non-financial disclosures. In particular, policies that improve transparency and comparability may be more valuable than those focused only on expanding the number of reporting entities.

The limitations of the study should also be acknowledged. This research is based on a selected sample of the largest companies by revenue and covers a relatively short observation period. Future research should move beyond the mere presence of disclosure and employ advanced econometric and content-analytical approaches to assess the quality, credibility, and strategic relevance of sustainability reporting, particularly in transition economies characterized by evolving institutional and regulatory settings.

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Motivations for Private Investment in Cultural Heritage

Preliminary communication

Mojca Marc[1], Iana Bilynets[2], Sara Ražman[3], Katja Zajc Kejžar[4], Nina Ponikvar[5]

ABSTRACT

Private investment in cultural heritage remains limited despite increasing recognition of the sector's cultural, social, environmental, and economic significance. This paper explores why private actors engage selectively in heritage projects and proposes an initial value-creation framework to clarify the underlying dynamics. The study builds on insights from the HEI-TRANSFORM project (Heritage for Inclusive Sustainable Transformation), which revealed a notable scarcity of good-practice cases of private investment in Slovenia compared to more established public initiatives. Drawing on existing literature, the paper outlines an emergent conceptual model in which cultural, social, and environmental value creation precedes and enables economic outcomes and, ultimately, financial returns. The review of investor motivations shows that private decisions are shaped by a combination of financial expectations, identity-based attachments, reputational concerns, regulatory risk, and stewardship values. At the same time, many private investors focus narrowly on short-term financial metrics and overlook the foundational value layers that make long-term economic performance possible. By reviewing research on heritage economics, adaptive reuse, partnership models, and sustainability, the paper positions heritage investment as a multidimensional and sequential process rather than a solely market-driven transaction. The framework presented here is preliminary and forms part of an ongoing conceptual development, offering a basis for further refinement as additional empirical evidence becomes available.

1 *Associate Professor, School of Economics and Business, University of Ljubljana, Kardeljeva ploščad 17, 1000, Ljubljana, Slovenia, mojca.marc@ef.uni-lj.si*

2 *Researcher, School of Economics and Business, University of Ljubljana, Kardeljeva ploščad 17, 1000, Ljubljana, Slovenia, iana.bilynets@ef.uni-lj.si*

3 *Teaching Assistant, School of Economics and Business, University of Ljubljana, Kardeljeva ploščad 17, 1000, Ljubljana, Slovenia, sara.razman@ef.uni-lj.si*

4 *Full Professor, School of Economics and Business, University of Ljubljana, Kardeljeva ploščad 17, 1000, Ljubljana, Slovenia, katja.zajc@ef.uni-lj.si*

5 *Associate Professor, School of Economics and Business, University of Ljubljana, Kardeljeva ploščad 17, 1000, Ljubljana, Slovenia, nina.ponikvar@ef.uni-lj.si*

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1 Introduction

Despite the growing recognition of the multifaceted value of cultural heritage, investment in the sector continues to rely predominantly on public funding, while private investors remain only marginally engaged. Scholars have long noted that cultural heritage cannot be treated as purely a public good nor left entirely to market mechanisms, due to its mixed characteristics and the presence of non-excludable external effects (Council of Europe, 2005; Seaman, 2013). Against this backdrop, the limited participation of private actors raises important questions: what prevents greater private-sector involvement, and what motivates those who do choose to invest?

This paper examines the underlying causes of this investment gap. We propose that the persistent lack of private engagement may stem from an overly narrow focus on immediate financial returns and from the systematic undervaluation of the non-market effects generated by heritage assets. Private investors, as conventional economic theory suggests, typically base decisions on expected financial returns arising from market-based transactions. However, many of the benefits associated with cultural heritage, such as cultural identity, social cohesion, aesthetic value, environmental quality, and community well-being, are non-market in nature and materialise as externalities (Seaman, 2013). These benefits rarely appear in traditional investment assessments, even though they underpin broader economic performance and long-term competitiveness (Licciardi & Amirtahmasebi, 2012; Throsby, 2001). As a result, the full value-creation potential of heritage often remains obscured, reinforcing private investors' hesitancy.

Building on the existing literature, we propose that financial returns from heritage investment should not be viewed as self-standing or independent outcomes. Rather, they may emerge as a downstream consequence of prior cultural, social and environmental value creation. Evidence from organisations such as Historic England suggests that heritage-led regeneration can contribute to above-average business performance, increases in local property values, and the revitalisation of economic activity, but typically only when investment strategies are embedded within broader social, cultural, and community objectives (Historic England, 2023a). In other words, socio-cultural value may not simply accompany economic return but may create the very conditions that enable it.

This proposition is consistent with patterns observed across other sectors. Investments in organic agriculture, sustainable textiles, family-friendly workplaces, or cultural and sports sponsorships often begin by targeting non-market effects—such as improved health, environmental stewardship, or enhanced social engagement. Over time, they yield competitive advantages, improved profitability, and stronger financial performance (Cerciello et al.,

2023; Coelho et al., 2023; Javed et al., 2024; Li et al., 2023; Velez Osorio, 2024). The heritage sector, however, seldom frames investments through this value-creation sequence, and therefore may be missing opportunities to align private incentives with public and community benefits.

While scholarship has explored the roles of public, private, and non-profit actors in cultural heritage (Boniotti, 2023; Borin, 2016; Majamaa, 2008), as well as the complementary nature of market and non-market solutions (Seaman, 2013), less attention has been given to the deeper motivations that guide private investors. Existing studies suggest diverse motives ranging from philanthropy and community commitment to reputation building, nostalgia, or the pursuit of authenticity (Pasquinelli, 2021; Rezaei & Gholami Gowhareh, 2021). Corporate actors may behave as "heritage enhancers" or "heritage grabbers," depending on how they balance profit motives with social and cultural considerations (Pasquinelli, 2021). Financial institutions face reputational and compliance risks when projects negatively affect cultural heritage, which shapes their investment choices (Mason & Ying, 2020; Mason & Martindale, 2023). Hybrid financing models have also been proposed to address market failures in heritage, blending financial and non-financial instruments to leverage both economic and impact returns (Pickerill, 2024).

Despite these developments, private investors in the heritage sector continue to prioritise short-term economic outcomes, often overlooking the foundational role of intangible, non-market effects. If heritage investment is perceived solely as a financial transaction rather than a multidimensional value-creation process, the incentives for private engagement remain limited. We therefore propose a paradigm shift: private investment strategies in cultural heritage should explicitly aim to generate cultural and social impacts as a pathway to economic and financial returns, rather than treating these impacts as incidental or secondary. Recognising and incorporating broader value dimensions into investment decision-making may help unlock the transformative potential of heritage assets and foster more sustainable private-sector engagement.

Although research in cultural heritage economics recognises that heritage generates both market and non-market value, these dimensions are typically analysed in parallel rather than as part of a structured value-creation process. Existing studies document spillover effects, regeneration outcomes, governance arrangements, and diverse investor motivations, yet they do not sufficiently clarify how cultural and social value creation translates into economic performance and financial returns, or how this sequencing shapes private investment decisions. As a result, the mechanisms linking intangible heritage outcomes to investor behaviour remain conceptually underdeveloped.

To address this gap, the paper proposes a value-creation framework that conceptualises heritage investment as a sequential and layered process in which cultural, social, and environmental value creation precedes and enables economic outcomes and, ultimately, financial returns. The proposed framework constitutes an early-stage conceptualisation intended to stimulate further theoretical development and empirical validation. By integrating this sequencing logic with the literature on investor motivations, the study offers a clearer explanation of why private engagement remains limited and identifies conditions under which more sustainable private participation may emerge.

This conceptual reframing motivates the central research question guiding this paper:

RQ: What are the motives of private investors in cultural heritage?

By exploring this question, the paper seeks to clarify how private-sector motivations have been conceptualised, identify gaps in existing approaches, and outline how a value-creation perspective might enhance the understanding of why private investment remains limited and how it may be encouraged.

2 Methodology

This study adopts an exploratory and conceptually driven research design. It builds on empirical insights generated within the HEI-TRANSFORM project (ARIS grant J7-4641), which examined adaptive reuse in the Slovenian cultural heritage context. During stakeholder discussions and case mapping activities conducted within the project, very few examples of private investment in cultural heritage were identified as positive or exemplary practices. The predominance of publicly funded initiatives and the relative scarcity of visible private-led success stories raised questions about the underlying motivations of private actors who nevertheless choose to invest in cultural heritage.

This observation prompted a broader inquiry into how private investment in cultural heritage has been conceptualised in the academic literature and whether existing research adequately explains investor behaviour. To address this, the study undertook a targeted literature review aimed at identifying relevant theoretical and empirical contributions across heritage economics, public–private partnerships, adaptive reuse, regeneration studies, and sustainability research. The review followed an iterative and snowballing approach, beginning with key foundational works and expanding through citation tracking and thematic relevance. This strategy allowed the integration of diverse strands of scholarship that are typically discussed separately. Therefore, the framework was developed through a combined inductive–deductive process: empirical observations from the HEI-TRANSFORM project highlighted an explanatory gap, while existing theoretical contributions informed the structuring of the proposed value-creation sequence. It should be understood as a preliminary conceptualisation emerging from theoretical integration rather than as a fully validated model.

3 Conceptual foundations

3.1 Heritage as a public, private or hybrid good

Cultural heritage occupies a complex position within economic theory because it embodies characteristics of both public and private goods. Seaman (2013) argues that heritage cannot be neatly categorised as either, since it combines elements of non-rival and non-excludable public benefits with forms of access and control that can, in practice, be privatised. Visitors' enjoyment of monuments, landscapes, or historic neighbourhoods does not diminish others' ability to benefit, and a wide range of cultural, social, and environmental values, such as identity, pride, aesthetic meaning, and symbolic resonance,

are collectively experienced rather than individually consumed. At the same time, many heritage assets are privately owned or can be made excludable through entry fees, concessions, or restricted access, creating opportunities for market-based management.

This hybrid character produces several structural challenges. The existence of asymmetric information means that private owners often lack full knowledge of long-term restoration costs, regulatory obligations, or heritage value. Equally, the public sector often lacks insight into private business models or constraints. More importantly, heritage generates substantial positive externalities that cannot be captured by private investors. The socio-cultural and environmental benefits of restoration, ranging from community cohesion to aesthetic enhancement, neighbourhood revitalisation, improved place identity, and tourism spillovers, extend far beyond the investor's revenue base. Because these non-market benefits rarely appear in investment appraisals, private actors tend to underinvest relative to the socially optimal level.

Studies of sponsorship for architectural heritage show that the non-market value of heritage creates a structural misalignment between private incentives and societal benefits, resulting in fragile or unsustainable funding models unless supported by public frameworks or hybrid arrangements (Dolores et al.,2017; 2020). Research on adaptive reuse in historical landscapes also highlights that cultural, social, and environmental values are deeply interwoven and cannot be fully monetised within conventional financial assessments, even though they are essential to the long-term viability of reuse projects (Rossitti, et al., 2021). The socio-economic impact of privately led heritage restoration, such as job creation, tourism expenditure, and regional branding, substantially exceeds private financial returns, reinforcing the argument that cultural heritage functions as a hybrid good positioned between market and non-market domains (Murzyn-Kupisz, 2013).

This conceptualisation of heritage as a hybrid good underscores the need for complementary public policy and private initiative. It also provides a theoretical basis for examining investor motivations, since private incentives must be understood within a system where value is produced jointly but not captured symmetrically.

3.2 Roles of public, private and non-profit actors

Heritage governance is shaped by a constellation of actors whose roles are distinct yet interdependent. Seaman (2013) notes that public and private sector activities are best understood as complementary rather than substitutive. Public authorities establish the regulatory frameworks, protection measures, planning controls, and incentive structures that safeguard cultural significance and manage risks that private actors may not be equipped to absorb. In this sense, state involvement is not only a response to market failure but also a mechanism for preserving heritage's non-market values.

Private actors, in contrast, contribute financial resources, operational expertise, and innovative reuse strategies. They often drive adaptive reuse, hospitality development, and niche commercial activities that give heritage

sites new economic purpose. For example, in Tanzania, private business involvement in heritage tourism expanded commercial opportunities, but insufficient coordination with public authorities and communities led to conflict and mistrust, illustrating the fragility of market-led approaches where cultural values are insufficiently recognised (Masele, 2012). Financial institutions represent another important category of private actor: banks increasingly integrate cultural heritage considerations into their environmental and social safeguards, motivated largely by reputational, credit, and compliance risks (Mason & Ying, 2020). These standards shape which heritage projects receive funding and under what conditions, extending private involvement well beyond ownership or development.

The non-profit, or third sector plays an equally important role. Organisations such as foundations, trusts, and local associations often act as custodians of cultural meaning, articulating community values and mediating between public and private interests. They mobilise volunteers, run cultural programming, advocate for sensitive interventions, and sometimes take ownership of heritage assets when neither public authorities nor private investors have the resources or incentives to do so. Research on authenticity in adaptive reuse demonstrates that non-profit and community actors are essential for grounding interventions in local cultural values and avoiding the erosion of heritage meaning (Eshrati et al., 2017).

Taken together, these sectors form a heritage ecosystem in which no single actor can deliver sustainable preservation alone. Public authorities ensure stewardship and regulatory oversight; private actors bring capital and innovation; and non-profits safeguard values and social legitimacy. Understanding this ecosystemic interdependence is critical for analysing how private motives align, or fail to align, with broader societal goals.

3.3 Public–private–people partnerships in cultural heritage

Partnership models between public authorities and private actors have become increasingly important in cultural heritage. Traditional partnership arrangements, such as contracts for specific services, agreements for operating and maintaining heritage sites, or long-term collaborations where private entities design, build, and manage visitor facilities, have been adapted from infrastructure and urban development fields (Nijkamp et al., 2002). However, these models require modification in the heritage sector because cultural assets are finite, symbolically significant, and often protected by national legislation and international conservation frameworks (Licciardi & Amirtahmasebi, 2012).

In cultural heritage, partnership structures must therefore prioritise authenticity, conservation standards, and the safeguarding of cultural meaning, which places clear limits on commercial flexibility. Research shows that inadequate attention to these aspects can result in community resistance, regulatory complications, or reputational risk for private partners, as illustrated in cases where cultural values were insufficiently incorporated into development processes (Masele, 2012) and in international financing decisions that required cultural heritage safeguards (Mason & Ying, 2020).

Because heritage values are deeply embedded in local communities, recent scholarship highlights the importance of partnership models that explicitly include residents and civil society (Gustafsson & Amer, 2023). These public–private–people arrangements position communities not merely as beneficiaries but as contributors to planning, governance, and ongoing management. Studies of adaptive reuse reinforce this point: meaningful community involvement helps ensure that interventions respect cultural significance and maintain authenticity (Eshrati et al., 2017). Research on reuse of rural landscapes similarly shows that integrating local knowledge is essential for identifying culturally appropriate functions and strengthening long-term sustainability (Rossitti et al., 2021). Parallel findings from place-based regeneration research indicate that outcomes are more effective and accepted when they align with local identity and values (Xiang et al., 2025).

In cultural heritage, therefore, partnership models must extend beyond transactional or contractual arrangements. They function best when they combine public stewardship, private resources and expertise, and community participation, ensuring that economic objectives do not overshadow cultural significance. This understanding provides a basis for analysing private investors' motives within the broader governance systems that shape heritage investment.

4 Motivations of investors in cultural heritage

Understanding why private actors choose to invest in cultural heritage requires examining a diverse and often overlapping range of motives that extend beyond conventional financial reasoning. Although investment decisions are commonly framed around expectations of monetary return (Throsby, 2001), the literature demonstrates that heritage-related investments are shaped by a mix of economic, social, cultural, reputational, and identity-driven considerations. These motivations vary across types of investors, corporations, small businesses, individuals, philanthropic donors, financial institutions, and are strongly conditioned by regulatory requirements, community expectations, and the hybrid nature of heritage itself.

Financial motivations remain central for many investors. Corporate actors and commercial developers often enter heritage projects with expectations of direct revenues, improved property values, or opportunities for real estate, hospitality, or tourism-based income. For example, heritage hotels and restored residences can become successful commercial ventures, generating visitor spending, employment, and regional economic benefits (Murzyn-Kupisz, 2013). Yet these financial gains typically materialise only once cultural and social values have been restored or enhanced, indicating that purely profit-driven motives are insufficient to explain why investors commit to heritage projects (Throsby, 2001; Licciardi & Amirtahmasebi, 2012; Historic England, 2023a; Pendlebury, 2013).

A significant share of private heritage investment is motivated by non-financial or mixed-value considerations. Individual investors frequently cite attachment to place, nostalgia, cultural identity, or a desire to preserve meaningfully embedded landscapes or buildings. In Iran, for example, private

owners and sponsors of historic house restoration were driven not only by economic opportunity but also by cultural pride, responsibility toward heritage, and interest in authenticity (Rezaei & Gholami Gowhareh, 2021). Similar findings emerge from adaptive reuse research, where owners of traditional residential structures viewed heritage preservation as a form of stewardship that reinforced local identity (Eshrati et al., 2017). These cases highlight the emotional and symbolic dimensions of investment, which are typically absent from financial modelling but central to private decision-making.

Corporate donors and sponsors engage with heritage through reputation building, social legitimacy, and brand enhancement. Sponsorship frameworks for architectural heritage show that firms view alignment with heritage values as a means of strengthening corporate social responsibility portfolios and differentiating themselves in competitive markets (Dolores et al., 2017; 2020). In many cases, these investments operate at the intersection of philanthropic intent and strategic positioning, offering companies visibility, goodwill, and cultural alignment that strengthen non-financial performance indicators. The distinction between sponsorship as transactional and partnership as long-term engagement becomes particularly relevant here, as sustained partnerships indicate deeper motivations tied to identity, social purpose, and stakeholder relations.

A growing body of literature also highlights risk mitigation and compliance as key motivators for financial institutions and large corporate actors. Banks increasingly apply environmental and social safeguard frameworks to ensure that heritage is not adversely affected by the projects they finance. This focus is shaped by reputational risk, legal compliance, and the rising importance of environmental, social, and governance standards (Mason & Ying, 2020). Projects that threaten cultural heritage can impede access to finance, delay construction, and provoke community opposition, all of which create strong incentives for investors to support or preserve heritage rather than endanger it. In this context, investment in heritage may be less about value creation and more about avoiding reputational harm, aligning with global sustainability norms, and ensuring project viability.

The concept of “heritage enhancers” versus “heritage grabbers,” introduced by Pasquinelli (2021), offers a useful interpretive lens for understanding how investors’ motives relate to outcomes. Heritage enhancers adopt business models and governance practices that respect heritage values, engage communities, and align with cultural stewardship. In contrast, heritage grabbers prioritise short-term gains at the expense of authenticity or access. This distinction illustrates that investor motivation is not only about why actors invest but also how they balance competing value orientations, risk perceptions, and ethical considerations.

Motivations also differ between large-scale investors and small or local entrepreneurs. In rural and small-town contexts, small businesses and local investors enter heritage projects to support community development, stabilise local economies, or preserve familiar landscapes. This pattern appears in studies of place-based regeneration, where adaptive reuse is often driven by local actors seeking to maintain identity, revitalise declining centres, or respond to community demand (Xiang et al., 2025; Gustafsson, 2019). Such

investments frequently operate with lower expected financial returns than large corporate projects, reflecting motives centred on belonging, continuity, and embeddedness.

Philanthropic motives constitute a further category, particularly in cases where individuals or foundations support heritage preservation for moral, cultural, or bequest reasons. As research in cultural economics suggests, donors are often motivated by intrinsic satisfaction, institutional trust, and social recognition rather than by tax incentives alone (Bertacchini et al., 2017). These motives align with the broader understanding of heritage as a cultural good whose value extends across generations.

Across all these investor categories, the literature points to a recurring tension between short-term financial expectations and long-term value creation. Many investors remain focused on immediate economic outcomes, while the broader social and cultural impacts that enable economic value often unfold over longer periods and are difficult to monetise. This misalignment contributes to the persistent underinvestment in heritage identified in the introduction. The motivations discussed in this chapter demonstrate the need to situate private investment within a multidimensional value framework where cultural, social and environmental outcomes are recognised as integral rather than incidental to financial performance.

Taken together, existing research suggests that private investment in cultural heritage emerges from a combination of financial aims, risk considerations, cultural values, identity-driven motivations, reputation management, and commitments to place. These motives vary widely across investor types and national contexts, yet they consistently reflect the hybrid nature of heritage and the interdependence of market and non-market values. The following chapter builds on this foundation by examining how value creation in cultural heritage unfolds across cultural, social, economic, and financial dimensions, and how this affects the incentives and barriers faced by private investors.

5 Value creation in cultural heritage investment

The investment gap in cultural heritage is closely tied to how value is understood, produced, and captured. Heritage generates cultural, social, environmental, and economic benefits, but these forms of value do not emerge simultaneously nor accrue to the same actors. We argue that cultural, social and environmental value creation precedes and enables economic and financial returns, yet investors often assess projects as if these benefits were independent. This chapter outlines a value-creation logic that reframes heritage investment as a sequential and layered process.

While heritage economics and spillover research have recognised that cultural value underpins economic value (Licciardi and Amirtahmasebi, 2012; Ruijgrok, 2006; Throsby, 2001), this work does not articulate how these values evolve over time or how they interact with social and environmental dimensions. Similarly, studies in urban regeneration show that heritage-led revitalisation strengthens identity, pride, and social capital, which in turn contribute to economic outcomes (Evans, 2005; Historic England, 2023a; 2023b; Pendlebury, 2013), yet these

effects are typically treated as co-occurring rather than as components of a structured value-creation sequence. Research on social and community value, such as work by the UK Department for Digital, Culture, Media and Sport (DCMS, 2021), acknowledges non-market value generation but again stops short of conceptualising its temporal relationship to economic performance. The framework proposed here addresses this gap by positioning cultural, social, and environmental value creation as the foundational layer upon which economic vitality and financial returns depend. This perspective clarifies why investors who focus solely on short-term financial metrics risk overlooking the deeper value-creation processes that make heritage investment viable.

Cultural value forms the initial foundation. Restoration, adaptive reuse, and authenticity preservation strengthen the symbolic and identity-based significance of heritage assets. Research on adaptive reuse emphasises that projects succeed when interventions respect cultural meaning and reinforce the narratives embedded in buildings and landscapes (Eshrati et al., 2017). These cultural gains increase visibility, legitimacy, and attachment, and they generate the conditions for subsequent social value.

Social value emerges through enhanced community cohesion, increased public use and pride, and improved local quality of life. Private restoration projects often create broad social spillovers—employment, revitalised public spaces, shifts in local identity, that extend far beyond the individual asset (Murzyn-Kupisz, 2013). These social benefits strengthen place attractiveness and support the creation of diverse networks among residents, visitors, and businesses. They also help secure a “social licence to operate” (Breakey et al., 2025), which is particularly important in heritage contexts where legitimacy is tied to community expectations.

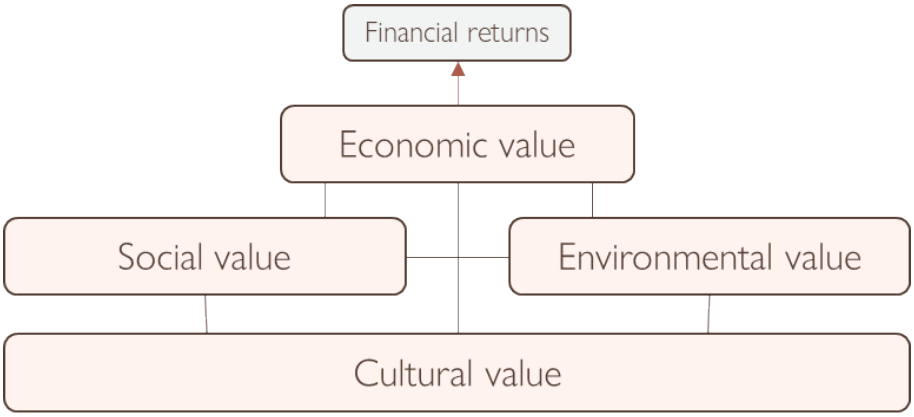
Heritage investment also generates environmental value through material conservation, reduced land consumption, adaptive reuse, and landscape protection. Reusing existing buildings lowers demolition waste, embodied energy, and lifecycle environmental impacts compared with new construction (Bullen and Love, 2011; Langston et al., 2008). Conserving building fabric further reduces resource use and carbon emissions while limiting urban sprawl by making more efficient use of already developed land (Douglas 2006; Conejos, Langston and Smith, 2013). Preservation of historic townscapes and cultural landscapes also strengthens ecological resilience and supports sustainable land management (Plevoets & Van Cleempoel, 2011). Heritage reuse is therefore widely understood as part of a multidimensional sustainability paradigm, where environmental, cultural, and social benefits reinforce one another (Murzyn-Kupisz, 2013; Rossitti et al., 2021). These environmental gains enhance the long-term attractiveness and operational efficiency of heritage sites, contributing indirectly to economic and financial returns.

Economic value materialises when cultural and social improvements translate into increased footfall, tourism demand, entrepreneurship, and strengthened local economies. Evidence from heritage-led regeneration, such as the transformation of historic residences into hospitality venues, shows that economic multipliers grow significantly once cultural and social foundations have been established (Murzyn-Kupisz 2013). Similar dynamics occur in rural landscape reuse, where revitalised cultural assets contribute to local

economic integration (Rossitti et al., 2021).

Financial outcomes appear last. They include direct revenues, return on investment, and long-term financial sustainability. Studies on sponsorship and heritage financing suggest that without prior investments in cultural and social value, financial payoffs remain limited or unstable (Dolores et al.,2017; 2020). Financial institutions implicitly recognise this sequencing: their risk assessments emphasise cultural heritage protection because damage to cultural or social value can generate reputational and credit risks (Mason & Ying, 2020).

Figure 1: Conceptual model of heritage value creation



Source: Authors

Understanding heritage investment through this layered value framework (Figure 1) challenges the assumption that financial returns drive heritage projects. Instead, economic and financial outcomes depend on earlier, often undervalued processes rooted in culture and community. For private investors, recognising these pathways offers a more realistic basis for evaluating long-term returns and identifying opportunities where cultural and social value creation can be intentionally leveraged as part of investment strategy.

6 Implications for policy and practice

The value-creation framework proposed in this paper differs from dominant market-centred perspectives in heritage economics, which often treat cultural and social impacts as externalities or parallel co-benefits of economically driven projects. While previous studies document spillover effects and regeneration outcomes, they frequently present these as accompanying economic performance rather than as foundational conditions for it. By conceptualising cultural, social, and environmental value creation as preconditions for economic viability and financial sustainability, this study reframes how private investment in heritage should be understood.

The layered value-creation process outlined in the previous chapter has significant implications for how cultural heritage investment should be governed, financed, and supported. If financial returns depend on earlier cultural, social and environmental value creation, then public policies, heritage institutions, and investment practices must be structured around enabling these foundational stages rather than expecting the market to generate them autonomously. This requires a shift from viewing private investment as a substitute for public responsibility toward recognising the interdependence of public frameworks, community engagement, and private-sector participation.

One clear implication is the need for policy instruments that recognise and support non-market value creation. Because cultural, social and environmental benefits cannot be fully monetised, investors are unlikely to undertake projects unless regulatory mechanisms or incentives reduce the gap between societal and private returns. Evidence from sponsorship models indicates that private firms are responsive to frameworks that make long-term engagement more predictable and less exposed to risk (Dolores et al., 2017; 2020). Similarly, research on reuse of cultural heritage shows that financial sustainability improves when evaluation methodologies integrate cultural values and local stakeholder perspectives from the outset (Rossitti et al., 2021). These findings support the introduction of targeted fiscal incentives, risk-sharing schemes, and hybrid financing structures that lower entry barriers for investors while ensuring that cultural and social value remain central.

A second implication concerns governance. Because cultural and social value emerge through participation, trust, and shared stewardship, investment frameworks must incorporate meaningful community involvement. Public–private–people partnerships offer a model for aligning economic viability with cultural legitimacy, particularly when communities are engaged early and consistently. Studies of adaptive reuse demonstrate that projects respecting community identity and authenticity are more likely to gain public support, avoid conflict, and succeed in the long term (Eshrati et al., 2017). Similarly, place-based regeneration research shows that adaptive reuse contributes to revitalisation only when it resonates with local narratives and responds to local needs (Xiang et al., 2025). Embedding such participatory processes within governance structures therefore strengthens both cultural and financial outcomes.

A third implication relates to risk management. Financial institutions increasingly apply environmental and social safeguards to avoid reputational and credit risks associated with heritage damage (Mason & Ying, 2020). Policymakers can build on these practices by integrating cultural risk assessment into planning, permitting, and public funding criteria. This not only protects heritage values but also gives private investors clearer guidance, reducing regulatory uncertainty and reinforcing the sequencing of value creation.

Finally, the recognition that heritage generates broad public benefits underscores the continuing necessity of public investment. Relying solely on private capital is unlikely to produce sustainable results given the structure of heritage value. Public authorities therefore play a critical role in funding the cultural, social and environmental groundwork, research, conservation, community engagement, interpretation, and planning, that makes private

investment viable. Private projects often succeed economically only because they build upon a context shaped by public initiatives and long-term cultural investment (Murzyn-Kupisz, 2013).

These implications suggest that unlocking private investment in cultural heritage requires a coordinated approach that aligns incentives, integrates community involvement, and acknowledges the layered nature of value creation. Policies that foreground cultural, environmental and social value therefore should create the conditions in which private investment can flourish sustainably.

Moreover, the paper contributes theoretically by integrating fragmented strands of literature on heritage economics, investor motivations, and sustainability governance into a single explanatory framework. It introduces a sequencing logic that clarifies how non-market value layers become economically consequential over time, helping to explain why private investors focused narrowly on short-term financial metrics may underinvest in heritage assets. By making this value-creation mechanism explicit, the study strengthens the conceptual basis for aligning private incentives with long-term heritage sustainability.

This study is conceptual in nature and does not empirically test the proposed framework. The value-creation sequence should therefore be understood as an analytical model that requires further empirical validation across different contexts, investor categories, and governance systems. Future research could examine longitudinal case studies to assess whether cultural, environmental and social value creation systematically precedes economic and financial performance, and how investor motivations evolve over the lifecycle of heritage projects.

7 Conclusions

This paper examined why private investment in cultural heritage remains limited and proposed a value-creation perspective to illuminate the underlying dynamics. In doing so, it advances a conceptual framework that clarifies the sequential relationship between cultural, social, environmental, economic, and financial value in heritage investment. Cultural heritage produces a wide spectrum of cultural, social, environmental, and economic benefits, yet these forms of value do not emerge at the same pace. Research shows that adaptive reuse and conservation should first generate cultural meaning, social cohesion, and environmental sustainability before contributing to broader economic impacts (Bullen & Love, 2011; Murzyn-Kupisz, 2013). Despite this sequence, investment decisions often prioritise immediate financial returns, overlooking the foundational processes that make such returns possible. This mismatch between how value is created and how it is assessed helps explain why private engagement remains insufficient.

The analysis of investor motivations demonstrates that private actors are driven by a mix of economic goals, reputational considerations, identity-based attachments, and stewardship values. Corporate sponsors may seek legitimacy or brand enhancement (Dolores et al., 2017), while financial institutions are

influenced by environmental and social safeguards and the reputational risks associated with heritage damage (Mason & Ying 2020). Local investors and individual owners frequently value authenticity, community identity, and continuity (Eshrati et al. 2017). These varied motivations, however, operate within governance and financing structures that do not consistently support the early cultural, social, and environmental value creation on which long-term economic performance depends.

The value-creation model developed in this paper helps clarify this misalignment. Recognising cultural, social, and environmental value as preconditions for economic and financial outcomes shifts attention away from narrow, market-based assessments and toward the broader processes that make heritage investment viable. This framing underscores the continued importance of public stewardship, community engagement, and enabling policies. Evidence from sustainable heritage management highlights that integrated approaches—combining regulatory protection, incentives, and participatory governance—are more likely to generate conditions favourable for private investment (Rossitti et al., 2021).

Overall, the findings suggest that unlocking private investment in cultural heritage requires coordinated action across public, private, and community actors. Financial returns cannot be isolated from the cultural, social, and environmental values that precede them. Policies and practices that acknowledge this interdependence can better align incentives, reduce risk, and support more sustainable forms of private participation. This perspective provides a foundation for future research on investment models and governance arrangements capable of balancing heritage conservation with long-term economic vitality.

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Irrational Consumer Behaviour in the Digital Economy: Behavioural Insights, AI Influence and Policy Implications

Preliminary communication

Laura Mandić[1], Stella Suljić Nikolaj[2], Dario Maradin[3]

ABSTRACT

This paper examines irrational consumer behaviour with the aim of providing a deeper understanding of systematic deviations from the assumptions of classical economic theory. The theoretical framework is based on the concepts of rationality and utility maximisation, and addresses their limitations in real-world decision-making. By integrating insights from behavioural economics, the paper highlights the role of cognitive biases, heuristics, and emotions in shaping consumer choices. Particular emphasis is placed on key mechanisms such as the anchoring effect, loss aversion, the endowment effect, the paradox of choice, and impulse buying. In the context of digital transformation, the analysis further explores how AI-driven platforms, algorithmic recommendations, and personalised marketing strategies shape consumer decision-making and amplify behavioural biases. The applied section examines real-world market phenomena, including Black Friday and digital marketing practices, as well as their implications for business strategies and public policy design, with a focus on the application of Nudge theory. The findings suggest that irrational consumer behaviour follows predictable patterns that are increasingly reinforced in digital environments. Understanding these patterns is essential for developing more effective marketing strategies and designing public policies that reflect actual decision-making processes. The paper contributes to the integration of classical and behavioural approaches by situating consumer behaviour within the broader context of digital transformation and AI-driven economic environments.

***Keywords**: Heuristics, Cognitive biases, Decision-making, Digital platforms, AI-driven systems*

1 *Student, University of Rijeka, Faculty of Economics and Business, Ivana Filipovića 4, 51000 Rijeka, Croatia. E-mail: laura.mandic21@gmail.com.*

2 *Assistant Professor, University of Rijeka, Faculty of Economics and Business, Ivana Filipovića 4, 51000 Rijeka, Croatia. Department of Finance and Banking. Phone: 0038551355143. E-mail: stella.suljic.nikolaj@efri.uniri.hr.*

3 *Associate Professor, University of Rijeka, Faculty of Economics and Business, Ivana Filipovića 4, 51000 Rijeka, Croatia. Department of Economic Theory. Phone: 0038551355184. E-mail: dario.maradin@efri.uniri.hr.*

***JEL classification**: D11, D91, E71*

1 Introduction

Consumer behaviour is a central area of research in microeconomics, as it reveals how individuals allocate limited resources to satisfy their needs and desires. Traditional economic approaches have long relied on the assumption of a rational consumer - homo economicus - implying that individuals possess complete information, clearly defined preferences, and make decisions aimed at maximising their personal utility. Based on these assumptions, models were developed that enabled precise explanations of market processes and predictions of consumer behaviour. However, everyday experience and extensive empirical evidence show that consumer decisions often deviate from these idealised models. Individuals face information shortages, time constraints, and limited cognitive capacities when making decisions. In addition, their choices are shaped by emotions, social pressures, and psychological biases. As a result, contemporary economic science recognises that rationality is limited in practice and that consumers frequently exhibit behaviour that can be classified as irrational. In the context of digital transformation, consumer decision-making is increasingly shaped by AI-driven platforms, algorithmic recommendations, and personalised marketing strategies. These technologies not only shape information availability but also structure choice environments, amplifying behavioural biases.

This research analyses deviations from the rational model of decision-making, with particular emphasis on irrational consumer behaviour and the influence of emotions, biases, heuristics, and social factors. It further examines how marketing strategies draw on behavioural insights to shape consumer choices and how a deeper understanding of irrationality can contribute to the design of more effective public policies.

The aim of the paper is to provide a systematic overview of the theoretical and practical aspects of irrational consumer behaviour and to connect traditional microeconomic models with more recent insights from behavioural economics.

To clearly articulate the contribution of the paper and guide both the theoretical and applied analysis, the study is structured around the following research questions:

RQ1: Why and in which ways do real consumer decisions deviate from the assumptions of rational behaviour in classical economic theory?

RQ2: Which behavioural biases and heuristics explain systematic patterns of irrational consumer behaviour?

RQ3: In what ways do marketing strategies and AI-driven digital environments activate these behavioural mechanisms?

RQ4: How can insights from behavioural economics contribute to more effective public policy design in the digital economy?

These research questions define the main contribution of the paper by linking classical economic theory, behavioural mechanisms, and digital market environments.

Methodologically, the paper is based on an analysis of relevant domestic and international scientific literature and a comparative consideration of classical and behavioural theoretical approaches. The interpretation uses practical examples that serve as illustrations of theoretical concepts, and the methods of analysis, synthesis and comparison are applied with the aim of providing a comprehensive overview of the complexity of the consumer decision-making process.

The paper is structured into five related sections. Following the introduction, the second section presents the theoretical foundations of consumer behaviour within the classical economic framework, focusing on rationality, utility theory, and the basic assumptions of decision-making. The third section introduces behavioural economics and explains how psychological factors, emotions, and heuristics influence consumer decisions. It also examines common examples of irrational behaviour in real market settings and discusses their implications for marketing and public policy. The fourth section builds on this by presenting selected case studies and by showing how behavioural insights can be applied in practice, particularly in the understanding of market behaviour and in designing policies. Finally, the fifth section summarises the main findings and brings together the key theoretical and practical insights of the paper.

2 Classical perspectives on consumer behaviour

Within the classical economic doctrine, the consumer is viewed as a rational actor who allocates limited resources in order to achieve the highest possible level of utility. The fundamental assumption is that individuals strive to optimally distribute their income among available goods and services. On this basis, theoretical models have been developed to explain the consumer decision-making process and to provide insight into the key characteristics of rational behaviour and the role of utility in consumption choices.

In classical theory, preferences are assumed to be complete and transitive, ensuring the internal logical consistency of choices, while utility maximization represents the guiding principle in decision-making. Under these conditions, consumer behaviour can be modeled within optimization frameworks in which individuals choose a bundle of goods that maximizes their utility subject to a given budget constraint. These assumptions have enabled economists to construct formal models that explain consumer behaviour and predict market outcomes.

The rational consumer, homo economicus, implies consistent and logical decision-making aimed at maximizing utility. The rational consumers' preferences are clearly defined and stable over time, and they possess complete information, allowing them to process it without cognitive limitations (Pindyck & Rubinfeld, 2013). Such a consumer has a certain level of income, which is allocated among available goods and services in a way that yields the highest level of satisfaction (Varian, 2014). The stability in preferences over time ensures predictability in decision-making (Nicholson & Snyder, 2014); thus, this consistency allows for the development of theoretical models to analyze consumer behaviour and predict the effects of changes in prices or income.

In classical theory, preferences are considered complete and transitive. Completeness implies that consumers are capable of evaluating and comparing all available alternatives, while transitivity ensures the internal consistency of their choices. This means that if a consumer prefers good A to good B, and good B to good C, then they must also prefer good A to good C (Mankiw, 2018).

Theories of consumer behaviour within the classical economic doctrine have been developed to explain how individuals make consumption decisions. The central concept in these theories is utility, which can be understood through two basic approaches: cardinal and ordinal utility. The cardinal concept assumes that utility can be measured in abstract units, often referred to as "utils," allowing for quantitative comparisons of satisfaction levels. For example, a consumer may estimate that a cup of coffee provides ten units of utility, while a cup of tea provides six, indicating a higher level of satisfaction from coffee.

In contrast, the ordinal concept of utility does not attempt to measure the intensity of satisfaction but instead focuses on ranking preferences. Within this framework, a consumer simply prefers coffee to tea without quantifying the difference in utility. The ordinal approach has become dominant in economic theory because it more accurately reflects how individuals make decisions in practice (Nicholson & Snyder, 2014).

Preferences, which play a key role in the analysis of consumer behaviour, are represented using indifference curves. Optimal consumption is achieved at the point of tangency between the budget constraint and the highest attainable indifference curve.

Although analytically powerful and theoretically coherent, this model relies on simplified assumptions that do not always reflect real-world decision-making processes. The assumption of fully rational and perfectly informed individuals represents an idealized theoretical benchmark rather than an empirically confirmed description of actual behaviour. Contemporary research increasingly suggests that individuals face information asymmetries, uncertainty, and cognitive limitations that influence their decisions and lead to systematic deviations from the rational model (Suljić Nikolaj et al., 2026).

2.1 Limits of rationality and market influences

Contemporary research increasingly questions the realism of the assumption of rationality and highlights its theoretical limitations (Jurak, 2021). In practice, individuals' decisions are shaped by a combination of rational motives, psychological influences, emotional responses, and social pressures. These factors interact in complex ways, leading to choices that may contradict the predictions of classical economic theory. Importantly, such deviations from rationality are not random but follow recognizable patterns.

Herbert A. Simon introduced the concept of bounded rationality to explain the gap between theoretical models and actual human behaviour. According to Simon, individuals strive to act rationally, but their rationality is limited by insufficient information, constrained cognitive abilities, and finite time. As a result, consumers do not aim to maximize utility but rather to find solutions that

are “good enough.” This decision-making strategy is known as satisficing and represents a practical compromise between theoretical ideals and real-world constraints (Simon, 1957).

The concept of bounded rationality emphasizes that decision-making is not solely the result of logical analysis but is shaped by mental limitations and environment structure. In practice, consumers rely on simplified decision rules and heuristics to cope with complex situations (Gigerenzer & Gaissmaier, 2011). While these strategies reduce cognitive effort, they also increase the likelihood of systematic errors.

Real-world decision-making is constrained by several well-established factors, most notably information asymmetry, time pressure, and cognitive limitations (Akerlof, 1970; Simon, 1955; Kahneman, 2011; Stiglitz, 2000).

One of the key limitations relates to the availability and quality of information. In real markets, information asymmetry is widespread, meaning that consumers often lack complete knowledge about product characteristics, prices, or the long-term consequences of consumption decisions (Akerlof, 1970). Since collecting and processing information is costly and demanding, individuals frequently rely on heuristics such as brand recognition, price signals, or recommendations from others (Tversky & Kahneman, 1974; Kahneman, 2011).

Time constraints represent another important factor influencing decision-making. In everyday environments characterized by numerous alternatives and limited time resources, consumers are unable to conduct a thorough evaluation of all available options. Consequently, they tend to choose satisfactory rather than optimal alternatives, consistent with Simon’s concept of satisficing behaviour (Simon, 1955).

Cognitive limitations further shape decision-making processes. Individuals face constraints related to attention, memory, and information-processing capacity, which prevent them from fully analyzing complex choice sets. As a result, decisions often reflect practical compromises rather than theoretically optimal outcomes (Kahneman, 2011).

These limitations are particularly evident in complex financial decisions, such as selecting insurance policies. Faced with extensive contractual information and limited expertise, consumers may rely on previously advertised offers or recommendations from agents. Although such choices may not be optimal in a normative sense, they can be considered “good enough” under real-world conditions, illustrating how informational, temporal, and cognitive constraints jointly influence consumer behaviour (Simon, 1957; Mullainathan & Thaler, 2000).

2.2 Marketing stimuli and irrational behaviour

The role of marketing in consumer behaviour extends beyond the rational aspects of purchasing. Marketing also operates on emotional, psychological, and social levels, making it a powerful factor in shaping decisions that deviate from classical assumptions of rationality.

In modern market conditions, marketing serves as a key instrument for influencing consumer behaviour. Its function goes far beyond merely providing information about products and services; it systematically affects perceptions of value, shapes preferences, and guides decision-making processes. Unlike classical economic assumptions, marketing strategies are based on an understanding of psychological and emotional factors that often lead consumers to make decisions that depart from utility maximisation (Kotler & Keller, 2016).

Through various instruments, such as pricing strategies, brand identity, and advertising campaigns, marketing creates an environment in which consumers respond to stimuli that are not necessarily linked to objective product characteristics. As a result, systematic biases, impulsive decisions, and long-term brand loyalty emerge, confirming that marketing acts as a strong stimulus for irrational consumer behaviour. Price is not merely a reflection of the monetary cost of a product or service, but also an important signal that shapes consumers' perceptions of value. In practice, consumers rarely base decisions solely on rational comparisons of price and quality; instead, their perceptions are influenced by psychological and social factors.

A substantial body of research indicates that higher prices create an impression of superior quality and exclusivity, even when objective differences between products are minimal (Zeithaml, 1988; Rao and Monroe, 1989; Dodds et al., 1991). This relationship reflects the role of price as a salient extrinsic cue that consumers use to infer product value under conditions of uncertainty (Darke & Chung, 2005). More recent studies confirm that price continues to function as a powerful signal of perceived quality and value in contemporary markets, particularly in digital environments characterised by information overload and reduced ability to evaluate intrinsic product attributes (Martinčić et al., 2022).

This phenomenon is particularly evident in the luxury goods market, where consumers purchase not only a product but also a symbol of prestige and status. Conversely, products with very low prices are often perceived as inferior or unreliable despite comparable quality (Levrini et al., 2021). In addition, psychological pricing strategies, such as setting prices just below round numbers (e.g., €19.99), exploit cognitive biases in numerical processing, leading consumers to perceive prices as significantly lower than they actually are and thereby increasing purchase likelihood (Thomas & Morwitz, 2005).

Branding plays a significant role in consumer decision-making, as brands represent more than just products; they embody values, emotions, and symbolic meanings. Consumers often rely on brand perception to simplify choices and reduce uncertainty, even when more economically rational alternatives exist. A brand is not merely a name or logo, but a symbolic construct that connects a product with specific emotions and values (Aaker, 1996). This intangible dimension creates value in the minds of consumers and leads to decisions based on perception rather than objective comparison. Brand loyalty often results from emotional attachment, trust, habit, or social identity, which can lead to irrational purchasing behaviour (Keller, 2013).

A common example is the loyalty of Apple users. Many consumers continue to purchase Apple products despite competitors offering devices with better

technical specifications at lower prices. Their decisions are driven by brand trust, perceived quality, and a sense of belonging to a particular social group, rather than purely rational cost–benefit analysis.

Advertising is one of the most powerful tools companies use to influence consumer perception and behaviour. Its purpose goes beyond providing information, aiming to elicit emotional responses and create associations between consumers and brands.

The psychological effects of advertising are particularly evident through repetition, as frequent exposure to a message creates familiarity and trust, regardless of actual product quality. Advertisements also rely heavily on emotional appeals, such as portraying family moments, success, or happiness, encouraging consumers to associate products with positive emotions (Kotler & Keller, 2016). They further reinforce these appeals by using images of socialising, enjoyment, and positive emotions. Consequently, when consumers choose such products, their decisions are influenced more by emotional associations than by rational evaluation of benefits and costs.

3 Behavioural economics as a theoretical framework

Behavioural economics emerged in response to the limitations of traditional economic theory, which often portrayed consumers as fully rational actors. In reality, human decisions are not always perfectly logical or based solely on cost-benefit analysis. Emotions, habits, social influences, and limited cognitive capacities significantly shape the decision-making process, which is why classical models do not fully explain market behaviour. In contemporary digital environments, these behavioural patterns are further reinforced by algorithmic systems that personalise content, prioritise information, and influence consumer attention. As a result, behavioural biases are not only present but are systematically amplified through AI-driven decision environments.

The primary objective of behavioural economics is to address this shortcoming by integrating psychological insights into economic analysis. It seeks to understand why consumers sometimes make decisions that appear irrational, how systematic errors in judgement arise, and how environmental factors can influence choice. In this way, behavioural economics not only expands the theoretical framework but also has practical value, as it helps design more effective marketing strategies and public policies grounded in actual patterns of human behaviour.

Within the behavioural framework, biases and heuristics represent the core mechanisms through which deviations from the rational model occur (Suljić Nikolaj, 2026). Biases can be classified into emotional, cognitive, and social categories (Schinckus, 2012). Emotional biases arise from affective responses and psychological reactions; they operate largely unconsciously and are therefore particularly difficult to correct. Importantly, they may persist even when individuals have access to complete information (Sapkota, 2023).

Cognitive biases, in contrast, represent systematic errors in reasoning that stem from the use of mental shortcuts. As such, they directly affect decision-making processes and may contribute to observable market distortions and

anomalies (Acciarini et al., 2021). Social biases emerge from the influence of social norms, majority opinions, and group behaviour. In these cases, individuals tend to rely on the actions and judgements of others, often neglecting their own information and analysis in order to conform, reduce perceived risk, or avoid missing opportunities (Jones & Roelofsma, 2000). Heuristics, as defined by Dale (2015), represent simplified modes of thinking grounded in prior experience that enable individuals to make faster decisions in complex situations by reducing the amount of information that needs to be processed. Although they can be adaptive and effective, relying on them often leads to systematic distortions in judgment. Accordingly, heuristics function as underlying cognitive mechanisms, whereas biases constitute the predictable outcomes generated by those mechanisms. To provide a structured overview of the key behavioural mechanisms discussed, Table 1 summarises the main consumer biases and heuristics, together with their underlying mechanisms and typical market manifestations.

Table 1: Overview and explanation of consumer biases and heuristics

Category	Bias / Heuristic	Mechanism	Market Manifestation
Emotional Bias	Loss aversion	Losses are perceived as more significant than equivalent gains	Fear of missing discounts; urgency during Black Friday
	Endowment effect	Ownership increases perceived value	Free trials increase attachment and purchase likelihood
	Self-control bias	Conflict between short-term impulses and long-term goals	Impulse buying; overspending during promotions
	Overconfidence	Overestimation of one's judgement	Risky purchasing decisions; excessive consumption
Cognitive Bias	Anchoring bias	Reliance on initial information	"Original price" framing in discount strategies
	Availability bias	Judging based on easily recalled information	Media-driven trends influencing product demand
	Representa-tiveness bias	Judgement based on stereotypes	Brand-based assumptions about quality
	Framing effect	Decisions depend on presentation	"Limited offer" vs "20% probability of discount"
	Mental accounting	Separate treatment of money	Spending bonuses or refunds more freely

Category	Bias / Heuristic	Mechanism	Market Manifestation
Social Bias	Herd behaviour	Following majority actions	Mass purchasing during Black Friday
	Social proof	Using others as reference	Online reviews influencing purchase decisions
	Information cascade	Ignoring own info to follow others	Viral product trends on social media
Heuristic	Anchoring heuristic	Initial value shapes judgement	Price comparison in retail and online platforms
	Availability heuristic	Ease of recall shapes perception	Overestimation of product popularity
	Representa-tiveness heuristic	Prototype-based judgement	Judging quality from packaging or brand image
	Affect heuristic	Decisions guided by emotion	Emotional advertising shaping brand preference
	Simulation heuristic	Ease of mental simulation shapes probability judgement	"Last chance" messages increase perceived probability of missing out and strengthen purchase intention.

Source: Authors, based on Kahneman and Tversky, 1979; Thaler, 1999; Kahneman and Tversky, 1982; Slovic et al., 2007; Kotler and Keller, 2016; Hausman, 2000; Solomon, 2020

However, behavioural findings are often context-dependent and may lack full generalisability across institutional and cultural environments, suggesting that the rational choice model can still serve as a useful analytical benchmark in certain settings.

3.1 Irrational forms of behaviour as evidence of behavioural economics

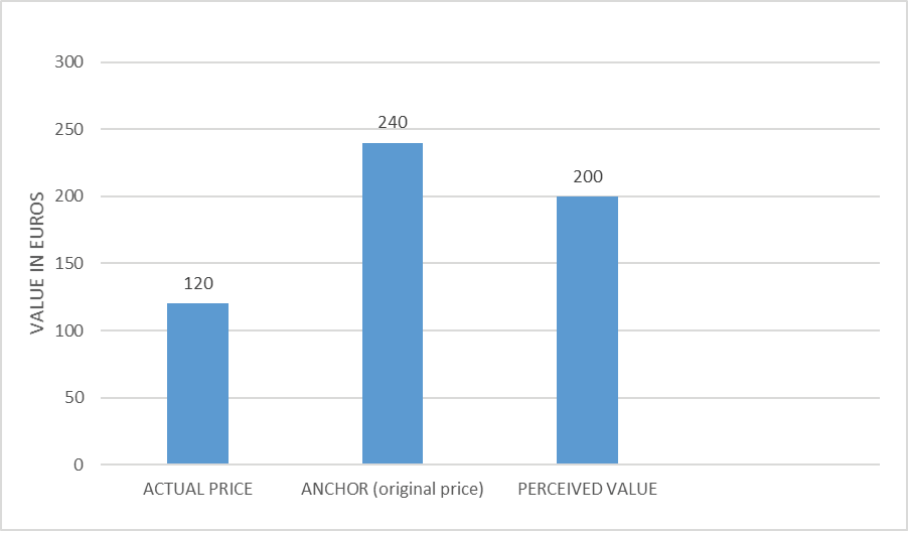
One of the most common forms of irrational consumer behaviour relates to the way initial information shapes subsequent decisions. People often rely on what is presented to them first, even when that information does not necessarily reflect the true value of a product or service. This bias is known as the anchoring effect. It is a cognitive bias in which the first piece of information, the so-called anchor, strongly influences subsequent value judgments and consumer decisions. When an initial price or value is presented, it is unconsciously internalized and becomes a reference point for comparison, even if it is unrelated to the product's objective value (Tversky & Kahneman, 1974).

In practice, the anchoring effect is most commonly used in pricing strategies. Firms deliberately set high initial prices to create a perception of value and then offer discounts or promotions that consumers perceive as significant benefits. In digital environments, this effect is even more pronounced: online retailers frequently display “old” crossed-out prices alongside new prices highlighted with colors or discount labels, further signaling to consumers that they are achieving substantial savings.

The anchoring effect is not limited to pricing; it also appears in negotiations and bargaining. When a seller sets an initial price significantly higher than what they are willing to accept, the buyer perceives any reduction as a personal gain, even if the final price remains relatively high. In this way, the anchor functions as a tool for manipulating perception by shaping the boundaries within which consumers make decisions. Psychologically, this effect is rooted in the human tendency to rely on heuristics and simple mental shortcuts. When faced with unfamiliar or complex decisions, such as evaluating the value of a product with an unknown true price, consumers use the first available information as a reference point. This process reduces cognitive effort but simultaneously leads to systematic bias in decision-making (Ariely, 2008).

The anchoring effect thus clearly demonstrates how strongly first impressions and context can shape consumer decisions. It reveals that decisions are not solely the result of rational analysis but also reflect psychological mechanisms and marketing tactics that deliberately exploit the human tendency to rely on initial information. The following figure illustrates the impact of the anchoring effect on the perceived value of a product.

Graph 1: The anchoring effect and product value perception



Source: Authors

Although the actual price of the sneakers is €120, the consumer is exposed to an anchor in the form of an original price of €240. As a result, the new price is perceived as highly favorable, leading the subjective valuation of the product to exceed its objective value. This discrepancy between objective and perceived value clearly highlights the importance of cognitive heuristics and emotional responses in consumer decision-making. Consequently, such influences lead to behaviour that deviates from the assumptions of rational decision-making and utility maximization, as defined in standard economic theory.

The endowment effect is another well-known form of irrational consumer behaviour and refers to the tendency of individuals to assign greater value to items they own compared to identical items they do not own. In other words, people often overvalue what they possess because the loss of an item is perceived more intensely than the pleasure of an equivalent gain, which is closely related to the concept of loss aversion (Kahneman et al., 1991).

Beyond laboratory experiments (Kahneman et al., 1991), the endowment effect has also been observed in real market settings. Empirical field studies show that individuals often assign higher value to goods they own compared to identical goods they do not own (List, 2003). Similarly, evidence from real estate markets indicates that property owners tend to set higher asking prices than buyers are willing to pay, reflecting emotional attachment and loss aversion (Genesove & Mayer, 2001; Plott & Zeiler, 2005). For example, consumers who purchase a product and use it for some time often evaluate it as more valuable than its market price, illustrating how ownership influences perceived value.

Loss aversion is a fundamental concept in behavioural economics and refers to the tendency of individuals to experience losses more intensely than gains of the same magnitude. This phenomenon was first systematically explained by Kahneman and Tversky (1979) through prospect theory, which demonstrated that, for example, the pain of losing $100 is greater than the pleasure derived from gaining the same amount. In this way, classical assumptions of rational behaviour are challenged, as individuals are shown to be driven not only by utility maximization but also by emotional responses to potential losses.

Empirical research provides strong support for the behavioural implications of loss aversion. One commonly used experimental paradigm is the mixed-gamble task, in which individuals are asked whether they would accept a 50–50 chance of winning or losing certain amounts of money. Empirical findings from prospect theory show that individuals frequently reject gambles with positive expected value (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). For instance, when offered a gamble that yields a gain of $11 if one outcome occurs but a loss of $10 if the alternative outcome occurs, most individuals choose to reject the gamble despite its favourable expected value (Kahneman & Tversky, 1979). This behaviour cannot be fully explained by standard expected utility theory and is instead interpreted as evidence of loss aversion (Rabin, 2000).

Within the traditional expected utility framework, such behaviour was initially interpreted as evidence of risk aversion (Samuelson, 1963). However, Rabin (2000) demonstrated that rejecting small-stakes mixed gambles would imply

implausibly extreme levels of global risk aversion, thereby challenging the explanatory power of standard models. These findings strengthen the interpretation that observed behaviour reflects loss aversion rather than conventional risk preferences, highlighting the psychological weighting of potential losses relative to gains.

Furthermore, neuroscientific research has confirmed that potential losses have a stronger impact on the brain than gains of the same magnitude. Tom et al. (2007) tracked participants' brain activity while they decided whether to accept or reject real monetary gambles. The results showed that brain regions associated with reward became more active as potential gains increased, while those same regions were more strongly suppressed when potential losses were expected. Responses to potential losses were particularly pronounced, confirming the existence of so-called neural loss aversion.

In today's market environment, consumers are confronted with an abundance of choices on a daily basis. Supermarkets, online stores, and other retail platforms offer dozens or even hundreds of variations of the same product, which at first glance may appear beneficial (Maradin et al., 2025). However, this raises the question of whether a greater range of options truly provides more freedom or, conversely, imposes an additional burden on consumers when making decisions.

The paradox of choice refers to a situation in which an increase in the number of available options does not lead to greater freedom and satisfaction but instead may cause stress, uncertainty, and decision deferral. Schwartz (2004) argues that modern markets, by offering an overwhelming number of alternatives, make decision-making more difficult for consumers, who must compare different products, prices, and quality levels. Instead of feeling free, many consumers experience frustration and lower satisfaction after purchase, as they question whether they chose the "best" option. For example, a consumer choosing among dozens of breakfast cereals may feel uncertainty and dissatisfaction, even if the selected product is objectively of high quality.

Schwartz (2004) distinguishes between two types of consumers: maximizers, who strive to find the best possible option, and satisficers, who are satisfied with finding an option that meets basic criteria. Maximizers are more prone to anxiety, dissatisfaction, and post-purchase regret, whereas satisficers tend to be more satisfied because they do not excessively analyze a large number of alternatives.

Empirical studies support the existence of this phenomenon. Iyengar and Lepper (2000) conducted a well-known experiment involving jam selection in a supermarket. When consumers were offered 24 different types of jam, more people stopped to examine the display, but fewer made a purchase. In contrast, when only six options were offered, fewer people stopped, but a significantly higher proportion made a purchase. This result clearly demonstrates that too many choices can hinder decision-making and reduce the likelihood of purchase.

Subsequent research suggests that the intensity of the paradox of choice depends on context. In a meta-analysis of more than 50 studies, Scheibehenne et al. (2010) concluded that the "too much choice" phenomenon is not universal

but varies depending on the type of product, the importance of the decision, and individual differences among consumers. For example, in important and high-stakes decisions such as choosing a university or buying a house, a larger number of options may lead to decision paralysis, whereas in everyday decisions, such as choosing a beverage, greater variety may have a positive effect.

The paradox of choice thus highlights that consumer decisions cannot be fully explained by the assumption of rationality. An excess of options often leads to emotional overload, underscoring the importance of incorporating psychological insights into the analysis of consumer behaviour.

In contemporary consumer environments, decisions are increasingly driven by immediate emotions and situational stimuli. The fast pace of modern life, constant exposure to marketing messages, and the widespread availability of digital platforms further contribute to consumers not always making deliberate or pre-planned decisions. In this context, the phenomenon of impulse buying emerges as a clear illustration of the link between emotions and consumer behaviour.

Impulse buying refers to situations in which consumers make decisions quickly, without prior planning or careful consideration of alternatives. Unlike the rational decision-making model, which emphasizes cost–benefit analysis, impulsive behaviour primarily arises from immediate emotional states and external stimuli. Emotions such as excitement, happiness, or even stress often exert a stronger influence than rational arguments, meaning that decisions are not based on maximizing long-term utility (Rook, 1987). Psychological research shows that impulse buying occurs when consumers are exposed to visual or promotional stimuli, such as attractive packaging, discounts, or limited-time offers (Hausman, 2000). For example, when a consumer encounters a shelf of chocolates labeled “today only -50% off,” the emotional response and sense of reward often lead to a quick purchase decision, even if the product was not on the planned shopping list. In online environments, this effect is even stronger, as digital platforms use personalized recommendations and one-click purchasing options, reducing opportunities for rational reflection.

Recent empirical studies further show that emotional arousal and pleasure significantly mediate impulse buying in digital environments, particularly among Generation Z consumers exposed to interactive product presentation formats (Ngo et al., 2024). The rapid expansion of live-stream shopping further amplifies impulse buying tendencies by combining social influence, entertainment stimuli, and real-time scarcity signals (Li et al., 2025). Consistent with these findings, recent meta-analytic evidence indicates that situational and marketing stimuli are the strongest predictors of online impulse buying behaviour in digitally mediated consumption contexts (Anoop & Rahman, 2025). Emotional decision-making is also reflected in the symbolic association of products with specific feelings and identities. Marketing campaigns frequently appeal to emotions such as happiness, security, or prestige, encouraging consumers to form affective connections with brands. In such contexts, purchasing decisions are driven less by functional product attributes and more by the symbolic meanings consumers assign to them (Hausman, 2000).

Impulse buying and emotional decision-making therefore clearly demonstrate how consumer behaviour deviates from the assumptions of rationality. They reveal that consumers are highly sensitive to psychological and situational factors, which has important implications for marketing practice as well as for the design of more effective public policies.

3.2 AI and digital platforms as amplifiers of behavioural biases

The rapid development of digital technologies has fundamentally transformed consumer decision-making environments. In particular, AI-driven platforms play an increasingly important role in shaping how individuals access information, evaluate alternatives, and make purchasing decisions. Unlike traditional market settings, digital platforms actively structure the choice environment through personalised content, recommendation systems, and algorithmic filtering. These technologies enable real-time data processing and predictive analytics, allowing firms to anticipate consumer preferences and adapt marketing strategies accordingly (Gupta, 2025).

Importantly, AI systems do not merely support decision-making but actively influence it. By prioritising specific products, highlighting selected price frames, and tailoring offers based on past behaviour, algorithms can reinforce existing cognitive biases such as anchoring, availability, and loss aversion. In digital environments, these biases are systematically embedded within algorithmic design, as personalised recommendations and targeted advertising increase the salience of certain options while limiting exposure to alternatives (Ali, 2025).

Recommendation systems represent a particularly powerful mechanism in this context, as they reduce search costs and cognitive effort while simultaneously guiding user attention. This creates a simplified decision environment that encourages heuristic-based processing rather than analytical evaluation. As a result, consumers are more likely to engage in impulsive and biased decision-making, consistent with the concept of bounded rationality. Furthermore, the increasing use of AI in marketing enables hyper-personalisation, where individual preferences are continuously monitored and predicted, thereby shaping consumption patterns in real time (Judijanto et al., 2024).

Recent research highlights that AI-driven systems can even influence consumer autonomy by subtly steering preferences and choices. The concept of the “algorithmic consumer” suggests that AI technologies interact directly with cognitive processes, influencing perception, attention, and evaluation mechanisms. This shifts the role of consumers from independent decision-makers towards participants in digitally structured environments where preferences are partially shaped by algorithms (Sifat, 2025). At the same time, the growing reliance on AI raises important concerns related to algorithmic bias and ethical implications. AI systems are trained on large datasets that may contain inherent biases, which can lead to distorted recommendations and unequal treatment of consumers. Moreover, the ability of AI-driven marketing to predict and influence behaviour raises questions about manipulation,

transparency, and consumer protection. In some cases, algorithmic systems may exploit behavioural vulnerabilities and override rational decision-making processes, particularly in high-frequency digital environments (Davtyan, 2026).

Consequently, AI-driven platforms do not simply reflect consumer preferences but actively shape them. This transformation has significant implications for both market efficiency and public policy, particularly in relation to digital market power, data governance, and the regulation of algorithmic decision-making. Understanding these dynamics is therefore essential for analysing consumer behaviour in the context of the digital economy.

4 Case studies and policy implications

The practical relevance of behavioural economics becomes particularly evident in large-scale market phenomena that systematically activate cognitive and emotional biases. Black Friday, for instance, illustrates how marketing stimuli interact with psychological mechanisms, leading to systematic deviations from utility-maximising behaviour under conditions of emotional and social activation (Simpson et al., 2011). Experimental findings in behavioural economics further confirm that such deviations are predictable rather than random. These insights are significant not only for businesses, but also for policymakers seeking to design more effective strategies that promote improved decision-making.

4.1 Black Friday as a manifestation of behavioural biases

In today's market environment, marketing campaigns significantly influence consumers and their behaviour. This is especially apparent when retailers use special events to stimulate mass consumption. One of the most prominent examples is Black Friday, which demonstrates how consumer decisions are shaped by emotions and marketing tactics rather than actual needs. In recent years, Black Friday has increasingly shifted to online platforms, where algorithm-driven promotions, personalised discounts, and real-time scarcity signals further intensify behavioural responses.

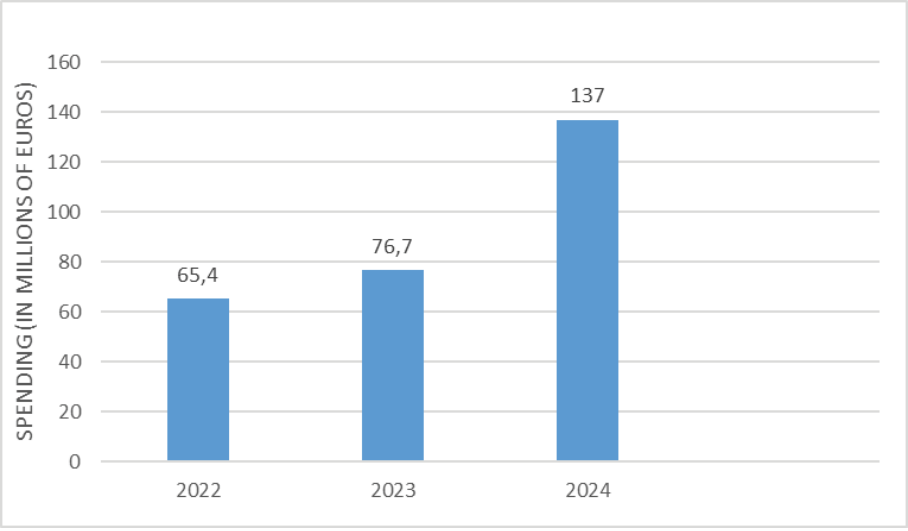
Originating in the United States in the mid-20th century, it has since spread worldwide. During this period, retailers implement strategically designed promotional campaigns, including discounts of up to 70%, promotional bundles, limited product quantities, and time-restricted offers. These tactics are designed to activate psychological mechanisms in consumers, such as the anchoring effect, the availability heuristic, and the fear of missing out (FOMO) (Alfina & Mardhiyah, 2023). This creates a perceived sense of urgency that encourages impulsive purchases, often without a rational assessment of actual needs (Kahneman, 2011).

Research shows that consumption increases significantly during Black Friday. For example, according to Adobe Analytics (2022), consumers in the United States spent over $9 billion on online shopping in a single day in 2022. This level of spending rarely reflects households' actual needs; instead, it

demonstrates the influence of emotional and cognitive biases. The anchoring effect is evident in the emphasis on high "original prices," making the new price appear extremely attractive, even though the actual savings are often minimal. At the same time, loss aversion leads consumers to perceive not making a purchase as missing an opportunity, further motivating them to buy (Tversky & Kahneman, 1979).

Marketing campaigns during Black Friday rely not only on discounts but also on specific psychological tactics. For instance, products are often advertised with statements such as "only 2 left in stock" or "offer valid while supplies last." This messaging activates the scarcity heuristic, whereby consumers perceive limited resources as more valuable, leading to a sudden increase in purchase intent. In online stores, personalised marketing is also used, with algorithms targeting products most likely to trigger impulsive purchases. Recommendation systems represent a particularly powerful form of digital nudging, as AI-driven algorithms personalise choice environments and increase the likelihood of impulsive purchasing by reducing search costs and cognitive effort (Jesse & Jannach, 2021). Practical examples confirm that these behavioural patterns are not isolated. During Black Friday, reports frequently describe overcrowded stores, extended waiting times, and occasional conflicts between consumers. These events illustrate the strong influence of emotional and cognitive triggers in contexts where market mechanisms actively engage behavioural biases. From an economic perspective, this demonstrates how marketing campaigns can create a situation in which rational cost-benefit analysis becomes secondary, while consumer behaviour is primarily shaped by psychological triggers and social pressures.

Graph 2: Black Friday in Croatia – Growth in consumer spending (2022–2024)



Source: Authors based on Statista data (2024)

The graph shows the trend in consumer spending in Croatia during Black Friday from 2022 to 2024. There was a significant increase from €65.4 million in 2022 to €76.7 million in 2023, representing a rise of approximately 17%. The largest increase occurred in 2024, when spending reached €137 million. This growth confirms the increasingly strong influence of marketing campaigns, discounts, and psychological mechanisms such as the FOMO effect and anchoring, which drive consumers towards impulsive and often irrational purchasing decisions.

4.2 Prospect theory and loss aversion

The development of behavioural economics is closely linked to the research of Daniel Kahneman and Amos Tversky, who introduced prospect theory in 1979, later expanded into cumulative prospect theory (Tversky & Kahneman, 1992). This theory emerged in response to the limitations of traditional expected utility theory, which assumed that individuals evaluate choices solely through rational calculations of expected outcomes. In contrast, Kahneman and Tversky demonstrated that people evaluate outcomes relative to a reference point (e.g., current income or status quo), rather than in absolute terms. One of the most important findings of their experiments was that losses have twice the psychological impact of gains of the same size. This phenomenon is called loss aversion.

A classic experiment involved a choice between a certain gain and a risky option (Kahneman & Tversky, 1979):

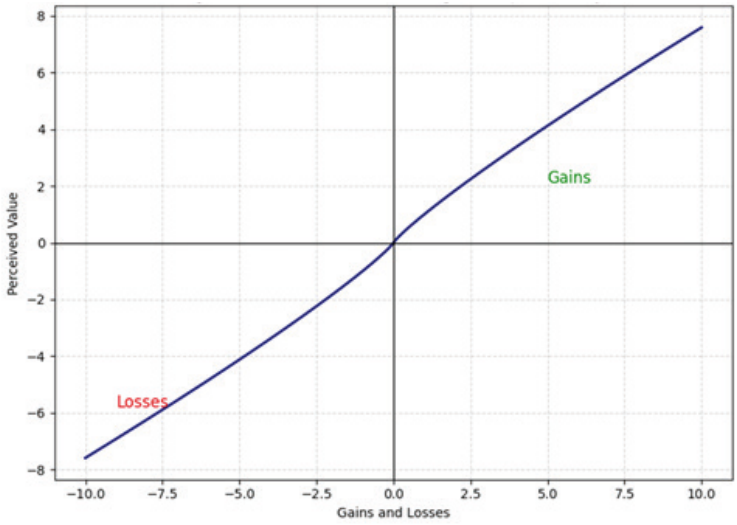
a) Participants could choose a sure gain of $500 or a 50% chance to win $1,000. Most chose the safe option, even though both options had the same expected value.

b) When the same experiment was framed in terms of losses, choosing between a sure loss of $500 or a 50% chance to lose $1,000, most participants chose the riskier option, seeking to avoid a guaranteed loss.

These results demonstrated that people exhibit risk aversion for gains but risk-seeking behaviour for losses. This deviates from classical theory predictions and explains why consumers and investors often behave irrationally in real-world conditions. Furthermore, prospect theory reveals other behavioural patterns, such as the certainty effect (preference for sure options even when they are not economically optimal), the isolation effect (tendency to focus on differences between options while ignoring shared elements), and probability weighting asymmetry. People often overestimate small probabilities (e.g., lottery winnings) and underestimate high probabilities, which further contributes to irrational decision-making (Kahneman, 2011).

Applications of prospect theory are evident in many areas: from insurance companies emphasising potential losses, to marketing strategies exploiting “last chance” offers, to public policy, where decisions are framed to highlight losses rather than gains to influence citizens’ behaviour.

Graph 3: Value function according to prospect theory



Source: Kahneman and Tversky, 1979

Value function according to prospect theory:

a) On the right side, there is a concave curve for gains, indicating that people become less sensitive to additional gains.

b) On the left side, there is a convex and steeper curve for losses, showing that losses are psychologically more significant than gains of the same size (loss aversion).

The graph illustrates the basic assumptions of Kahneman and Tversky's prospect theory (1979). The curve is concave in the domain of gains and convex in the domain of losses, with a steeper slope for losses. This means individuals experience diminishing sensitivity to gains, while losses of the same magnitude have a stronger negative impact. This asymmetry explains why people exhibit loss aversion and often make decisions that deviate from the predictions of classical expected utility theory.

4.3 Consumer behaviour in public policy

The role of consumer behaviour is not limited to the relationships between buyers and businesses; it also extends to broader social processes. The ways in which people make decisions about saving, health, education, or environmental protection have direct consequences for the community as a whole. For this reason, understanding consumer behaviour becomes an important element in shaping public policies aimed at guiding citizens towards socially beneficial and long-term sustainable choices.

Consumer behaviour plays a significant role not only in the business sector but also in the public sector, as it shapes how policies of broader social interest

are designed and implemented. Traditional economic models assumed that people make purely rational decisions aimed at their own well-being; for example, they would save for the future, invest in education and health, and use resources efficiently. In practice, however, it has been shown that people often act differently: they delay decisions, overvalue short-term gratification, and place long-term benefits in the background (Thaler, 1999).

Such deviations from the rational model create challenges for policymakers. Examples appear in the healthcare system, where many citizens neglect preventive check-ups or continue harmful habits despite knowing their consequences. In finance, it is common for people not to save or invest because they believe they can postpone the decision or because the process seems too complicated. Empirical evidence suggests that behavioural policy interventions can be highly cost-effective, often generating substantial improvements in decision-making outcomes compared to traditional regulatory approaches (Benartzi et al., 2017).

To overcome these patterns, insights from behavioural economics are increasingly applied. Instead of assuming that individuals will make rational choices on their own, policies are designed to account for citizens' limited rationality and psychological tendencies. An example is the system of automatic enrolment of employees in pension funds: citizens are enrolled by default, and opting out is possible only if they actively request it. Research has shown that this approach significantly increases savings rates because most people remain with the default option, illustrating the importance of the so-called "default effect" (Madrian & Shea, 2001).

A similar principle is applied in the energy sector. In the UK, experiments were conducted in which households received electricity bills with additional information comparing their consumption to that of their neighbours. Households consuming more than average received a message indicating they were using more than their neighbours, which led to a measurable reduction in energy consumption. This example clearly demonstrates how social comparisons and the desire not to deviate from norms can drive behavioural change (Allcott, 2011). These principles can also be applied to other policies. In taxation, this could involve clearer presentation of information or pre-filled forms, reducing errors and delays. In healthcare, clear reminders and incentives, such as free preventive check-ups or nutritional labelling of food, can promote healthier decisions.

From this, it follows that successful public policies should be based on actual human behaviour rather than solely on theoretical assumptions of rationality. By taking psychological and social factors into account, it is possible to design more effective measures that provide long-term benefits both to individuals and society as a whole.

4.4 The application of Nudge theory

Nudge theory, developed by Sunstein and Thaler (2008), is based on the idea that human behaviour can be guided through "choice architecture" – small incentives that make it easier for individuals to make decisions in their own

interest without restricting their freedom of choice. Recent research extends the concept of choice architecture to digital environments, showing that interface design, default options, and visual presentation in online platforms can systematically steer consumer decisions, a phenomenon known as digital nudging (Weinmann et al., 2016). Unlike traditional policies, which often rely on bans or strict regulations, the Nudge approach uses subtle changes in the environment to encourage citizens to make better decisions.

The application of this concept can be observed across several policy domains. In the field of finance, the introduction of automatic enrolment of employees in pension schemes in the United States and the United Kingdom has significantly increased participation and savings rates. Since enrolment is set as the default option, most individuals remain in the system, illustrating how default rules influence behaviour by reducing the need for active decision-making (Allcott, 2011; Madrian & Shea, 2001).

In the area of health policy, behavioural insights are applied through subtle modifications of choice architecture. In several European countries, including Denmark and the Netherlands, healthier food options are placed in more visible and accessible positions in cafeterias, while clear nutritional labelling facilitates quicker and more informed decisions. Such interventions do not restrict freedom of choice, but they steer consumers towards healthier outcomes.

Similarly, in the domain of environmental and energy policy, behavioural tools have been employed to encourage more responsible consumption. In countries such as the United Kingdom and Germany, households received electricity bills that included information comparing their energy use to that of their neighbours. Research demonstrated that households with above-average consumption subsequently reduced their usage, highlighting the influence of social comparison and normative cues on behaviour (Allcott, 2011).

Within the European Union, the application of the Nudge approach is receiving increasing attention, particularly in the areas of energy efficiency, plastic reduction, and healthy lifestyle promotion. Recent analyses by Blasco et al. (2024) highlight the systematic integration of behavioural insights into EU policy design, demonstrating how behavioural tools are increasingly embedded in regulatory and governance frameworks. At the international level, the OECD (2019) documents the broader institutionalisation of behavioural approaches in public governance across numerous countries.

Regarding Croatia, the institutionalised application of Nudge theory has not yet fully taken hold, but there are areas where it could have a significant impact. Examples include:

a) Tax policies: clearer forms and pre-filled tax returns could reduce errors and increase collection rates.

b) Health policies: preventive check-ups and vaccinations could be encouraged through personalised SMS reminders or simplified booking procedures.

c) Environmental policies: encouraging citizens to recycle through visual reminders and emphasising social norms (e.g., “80% of your neighbours

already separate their waste").

Implementing the Nudge approach in Croatian policies would require interdisciplinary collaboration between economists, psychologists, and public institutions. Although these are small steps, such incentives can have long-term social and economic effects because they guide citizens towards desirable decisions without limiting their freedom of choice.

A practical example can be seen in Zagreb, where in 2022 a new waste collection payment system based on city-branded bags was introduced (Zagrebački Holding – Čistoća, 2022; Balkan Green Energy News, 2022). Citizens paid for waste collection according to the number of bags they used, providing a financial incentive to reduce waste. While this system is often perceived as a fiscal measure, it also contains elements of the Nudge approach, guiding citizens to think more about the amount of waste they produce and to adopt recycling paractices more easily. The visual recognisability of the official bags further emphasised the importance of behavioural change, while messages about environmental preservation acted as a social reminder of responsible behaviour. This example illustrates how financial incentives combined with social signalling can function as behavioural nudges rather than purely fiscal instruments.

Such experiences demonstrate that the principles of behavioural economics can be successfully applied in the Croatian context, particularly when consumers are supported in making decisions that align with long-term societal goals.

5 Conclusions

Consumer behaviour is a complex phenomenon that cannot be fully explained by classical economic models alone. While these models assume a rational actor who makes decisions in line with utility maximisation, numerous studies and practical examples show that human decisions often deviate from this idealised framework. It is in this context that behavioural economics has emerged, as a discipline combining psychology and economics to explain real patterns of human decision-making.

The paper illustrates that consumers face a range of constraints every day, from time and cognitive limits to informational restrictions, which make optimal decision-making rare. Instead of systematically analysing all options, people rely on heuristics and mental shortcuts that simplify decision-making but also introduce biases and errors. Emotions also play a crucial role: feelings such as fear, excitement, regret, or euphoria can strongly influence choices, sometimes more than objective facts.

Examples such as the anchoring effect, endowment effect, loss aversion, choice overload, and impulse buying demonstrate that deviations from rational behaviour are not only common but also predictable. This shows that irrational behaviour does not occur randomly; it follows identifiable patterns that can be studied and understood. Marketing strategies and promotional campaigns further exploit these psychological mechanisms, explaining why phenomena like Black Friday have become a global symbol of collective,

irrational consumer behaviour.

It is important to note that understanding these patterns is useful not only for businesses in adjusting their strategies but also for policymakers. Applying insights from behavioural economics allows the design of policies that account for actual, rather than idealised, human behaviour. Examples such as automatic enrolment in pension funds, tax reminders, or energy consumption comparisons demonstrate that subtle incentives (nudges) can achieve greater efficiency and long-term social benefits. Even in the Croatian context, such approaches can be found, such as the waste collection system in Zagreb based on official city-branded bags, which guided citizens towards more rational resource management and recycling.

Behavioural economics significantly enriches classical theoretical models by providing a more realistic depiction of human behaviour. It shows that people are not perfectly rational, yet their "irrationality" is not chaotic; it is predictable and systematic. These insights have important implications for business strategies and public policy design. Future research should further examine the interaction between digital environments and behavioural biases, as algorithmic platforms increasingly shape consumer decision-making. In particular, the growing influence of AI-driven platforms raises important challenges related to digital market power, data governance, and the broader economic implications of algorithmic decision environments.

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