

Volume 13 (2025)

ISSN: 2300-5947

No. 3

FORUM SCIENTIAE OECONOMIA



Aleksy Kwilinski, Oleg Reznik

Governance of Artificial Intelligence Technologies and Systems in the EU and Ukraine: Legal Foundations and Institutional Mechanisms

Lukasz Sulkowski, Justyna Dziedzic, Sylwia Przytula, Robert Seliga

Revisiting Self-Determination Theory in the Prestige Economy of Science: Implications for Academic Motivation

Kemal Erkisi

The Moderating Role of Urbanisation in the Environmental Impact of Economic Complexity and Capital Formation: Evidence from OECD Countries

Bilal Hmoud, Ola Alhadid, George Sammour

Beyond Efficiency: Understanding Job Candidates' Acceptance of AI-enabled Recruitment: A Socio-Technical Perspectives

FORUM

Scientiae Oeconomia

Editorial Board:

Ilan Alon, Prof. – University of Agder (Norway)

Armenia Androniceanu, Prof. – The Bucharest University of Economic Studies (Romania) **Michaela Bednarova**, PhD – Pablo de Olavide University, Seville (Spain)

Joanne Bernstein, Prof. – Arts Marketing Insights (USA) **Piotr Białowolski**, Prof. – Harvard University (USA)

Ryszard Borowiecki, Prof. – Cracow University of Economics (Poland) **Cagri Bulut**, Prof. – Yasar University (Turkey)

Jorge Carneiro, Prof. – FGV Sao Paulo School of Business Administration (Brasil) **Daniele Cerrato**, Prof. – Catholic University of the Sacred Heart in Milan (Italy)

Federica Codignola Bo, Prof. – University of Milano-Bicocca (Italy)

Andrzej Cwynar, Prof. – University of Economics and Innovation in Lublin (Poland)

Szymon Cyfert, Prof. – Poznan University of Economics (Poland)

Joanna Cygler, Prof. – Warsaw School of Economics (Poland)

Dan-Cristian Dabija, Prof. – Babes-Bolyai University Cluj-Napoca (Romania)

Desislava Dikova, Prof. – Vienna University of Economics and Business (Austria) **Vasile Dinu**, Prof. – Bucharest University of Economic Studies (Romania)

Aiste Dovaliene, Prof. – Kaunas University of Technology (Lithuania)

Boris Durkech, Prof. – Armed Forces Academy of General Milan Rastislav Stefanik in Liptovsky Mikulas (Slovakia)

Ondrej Dvoutely, Prof. – University of Economics, Prague (Czech Republic)

Wojciech Dyduch, Prof. – University of Economics in Katowice (Poland)

Joanna Ejdys, Prof. – Bialystok University of Technology (Poland)

Maria Elo, Prof. – University of Southern Denmark (Denmark)

Carlos Fernandes, Prof. – Polytechnic Institute of Viana do Castelo (Portugal) **Pantea Foroudi**, Prof. – Middlesex University London (UK)

Juan J. Garcia-Machado, Prof. – University of Huelva (Spain)

Fabio Garzia, Prof. – SAPIENZA – University of Rome (Italy)

Jolita Greblikaite, Prof. – Vytautas Magnus University Agriculture Academy, Kaunas (Lithuania)

Philippe Gugler, Prof. – University of Fribourg (Switzerland)

Katarzyna Halicka, Prof. – Bialystok University of Technology (Poland)

Kathryn Rudie Harrigan, Prof. – Columbia Business School (USA)

Vladimir Hladlovsky, Prof. – Matej Bel University in Banska Bystrica (Slovakia)

Stefan Hittmar, Prof. – University of Zilina (Slovakia)

Gunter Hofbauer, Prof. – Technical University Ingolstadt, THI Business School (Germany)

Shuichi Ishida, Prof. – Tohoku University, Sendai (Japan)

Adam Jablonski, Prof. – WSB Universities (Poland)

Marek Jablonski, Prof. – WSB Universities (Poland)

Alfredo Jimenez, Prof. – Kedge Business School, Bordeaux (France)

Svatopluk Kapounek, Prof. – Mendel University, Brno (Czech Republic)

Anastasia A. Katou, Prof. - University of Macedonia, Thessaloniki (Greece)

Bilal Khalid, Prof. - King Mongkut's Institute of Technology Ladkrabang (Thailand)

Aleksandr KJucnikov, Prof. - University of Entrepreneurship and Law, Prague (Czech Republic)

Kim Lehman, Prof. - University of Tasmania (Australia)

Oscar Lopez de Foronda Perez, Prof. - University of Burgos (Spain) Edit Lukacs, Prof. - „Dunarea de Jos” University of Galati (Romania)

Oleksii Lyulyov, Prof. - Sumy State University (Ukraine)

Jana Majerova, Prof. - University of Zilina (Slovakia)

Viera Markova, Prof. - Matej Bel University in Banská Bystrica (Slovakia) Pedro A. Martín-Cervantes, Prof. - University of Almeria (Spain)

Ulrike Mayrhofer, Prof. - Universite Cote d'Azur, IAE Nice - Graduate School of Management (France)

Ieva Meidute-Kavaliauskiene, Prof. - Vilnius Gediminas Technical University (Lithuania)

Nikolay Megjts, Prof. - Webster University (USA)

Daniel Meyer, Prof. - University of Johannesburg (South Africa)

Navid Mollaei, PhD, MBA - Tehran Institute of Technology, Simia (Iran)

Juraj Nemec, Prof. - Masaryk University, Brno (Czech Republic)

Bogdan Nogalski, Prof. - University of Gdansk (Poland)

Judit Olah, Prof. - University of Debrecen (Hungary)

Maria Palazzo, Prof. - University of Salerno (Italy)

Marco Papa, Prof. - University of Bari (Italy)

Adrian Payne, Prof. - University of New South Wales (Australia)

Piotr Pikiewicz, PhD - WSB University (Poland)

Tetyana Pimonenko, Prof. - Sumy State University (Ukraine) Barbara Piontek, Prof. - WSB University (Poland)

Michal Placek, Prof. - Charles University, Prague (Czech Republic) Jozsef Popp, Prof. - Szent Istvan University (Hungary)

Diego Francisco Quer Ramon, Prof. - University of Alicante (Spain) Michael Radin, Prof. - Rochester Institute of Technology (USA)

Mladen Radiic, Prof. - University of Novi Sad (Serbia)

Matevz Raskovic, Prof. - Viktoria University of Wellington (New Zealand)

Nadine Roijackers, Prof. - Open University in Heerlen (Netherlands)

Sorab Sadri, Prof. - JECRC University, Jaipur (India)

Rachel Shane, Prof. - University of Kentucky (USA)

Nestor Shpak, Prof. - Lviv Polytechnic National University (Ukraine)

Ligita Simanskiene, Prof. - Klaipeda University (Lithuania)

Viktorija Skvarciany, Prof. - Vilnius Gediminas Technical University (Lithuania)

Frantisek Sudzina, Prof. - Aalborg University (Denmark)

Jindrich Spicka, Prof. - University of Economics, Prague (Czech Republic)

Adriana Roseli Wünsch Takahashi, Prof. - Federal University of Parana (Brasil)

Vasyl Taras, Prof. - University of North Carolina at Greensboro (USA)

Didier Van Caillie, Prof. - HEC School of Management, University of Liege (Belgium)

Maria del Carmen Valls Martinez, Prof. - University of Almeria (Spain)

Olena Vinnychuk, Prof. - Chernivtsi National University (Ukraine)

Zuzana Virglerova, PhD - Tomas Bata University, Zlin (Czech Republic)

Ivona Vrdoljak Raguz, Prof. - University of Dubrovnik (Croatia)

Jolita Vveinhardt, Prof. - Lithuanian Sports University / Vytautas Magnus University (Lithuania)

Anna Wziatek-Stasko, Prof. - Jagiellonian University (Poland)

Jeoung Yul Lee, Prof. - Hongik University (South Korea)

Michal Zabovsky, Prof. - University of Zilina (Slovakia)

Mirosław Zaborowski, Prof. - WSB University (Poland)

Peter Zamborsky, Prof. - University of Auckland (New Zealand)

Dariusz Zarzecki, Prof. - University of Szczecin (Poland)

Hongjun Zhao, Prof. - Shanghai Normal University (China)

Andrew Zimbroff, Prof. - University of Nebraska-Lincoln (USA)

Joze Zupancic, Prof. - University of Maribor (Slovenia)

Editorial Team:

Editor-in-Chief

Aleksy Kwilinski, Prof. - WSB University (Poland)

Deputy Editor in Chief

Katarzyna Szczepanska-Woszczyna, Prof. - WSB University (Poland)

Lukasz Wroblewski, Prof. - WSB University (Poland)

Karolina Mucha-Kus, PhD - WSB University (Poland)

Associate Editors

Marina Salesvik, Prof. - Western Norway University of Applied Sciences (Norway) Associate Editor - Europe

Mike Szymanski, PhD - Moscow School of Management SKOLKOVO (Russia) Associate Editor - South and Middle America

Kiminori Gemba, Prof. - Hosei University (Japan) Associate Editor - Asia

Adnan ul Haque, Prof. - Yorkville University, Concord, Ontario (Canada) Associate Editor - North America

Natanya Meyer, Prof. - University of Johannesburg (South Africa) Associate Editor - Africa

Language Editors

Andrew Gillin, MA - WSB University (Poland)

Barbara Borkowska-Kępska, MA - WSB University (Poland)

Editor for Statistics

Katarzyna Debkowska, PhD - Polish Economic Institute, Warsaw (Poland)

ISSN 2300-5947

Copyright © 2025 WSB University in Dąbrowa Górnicza. All Rights Reserved

Scientific Publishing of WSB University, Ciepłaka 1c, 41-300 Dąbrowa Górnicza, Poland

WSB University

FORUM

Scientiae Oeconomia

Vol. 13 [2025] • No. 3

Published by WSB University

Table of Content

1. Governance of Artificial Intelligence Technologies and Systems in the EU and Ukraine: Legal Foundations and Institutional Mechanisms Aleksy Kwilinski, Oleg Reznik.....	8
2. Revisiting Self-Determination Theory in the Prestige Economy of Science: Implications for Academic Motivation Lukasz Sulkowski, Justyna Dziedzic, Sylwia Przytula, Robert Seliga.....	53
3. The Moderating Role of Urbanisation in the Environmental Impact of Economic Complexity and Capital Formation: Evidence from OECD Countries Kemal Erkisi.....	68
4. Beyond Efficiency: Understanding Job Candidates' Acceptance of AI-enabled Recruitment: A Socio-Technical Perspective Bilal Hmoud, Ola Alhadid, George Sammour.....	89
5. Taste, Quality or Price? Investigating Consumer Patriotism in the Food Market Julia Wojciechowska-Solis, Aleksandra Kowalska.....	114
6. Financial Impacts of the COVID-19 Pandemic on the Cultural and Creative Industries: Evidence from Taiwan Liza Lee, Ying-Sing Liu.....	131
7. Identification of Key Indicators, Model Development, and Validation Methods for Bankruptcy Prediction: A Systematic Review for the Visegrad Group Sebastian Klaudiusz Tomczak, Michal Karas, Tamas Kristo, Lucia Duricova, Marek Durica.....	156

Governance of Artificial Intelligence Technologies and Systems in the EU and Ukraine: Legal Foundations and Institutional Mechanisms

Aleksy Kwilinski ^{1,*}, Oleg Reznik ²

¹ The London Academy of Science and Business, London, UK; Institute for Sustainable Development and International Relations, WSB University, Dabrowa Gornicza, Poland; Sumy State University, Sumy, Ukraine
ORCID: 0000-0001-6318-4001
e-mail: a.kwilinski@london-asb.co.uk

² Sumy State University, Sumy, Ukraine
ORCID: 0000-0003-4569-8863
e-mail: reznikoleg07@gmail.com

* Corresponding author: Aleksy Kwilinski, a.kwilinski@london-asb.co.uk

Abstract

The rapid advancement of artificial intelligence (AI) is transforming economic, managerial, and legal systems, creating new opportunities and risks for sustainable development and social equity. Within global digitalisation and Ukraine's integration into the European legal and technological framework, the study of AI development management becomes a key element of national digital transformation. The topic holds significant scholarly and practical importance as it bridges law, economics, management, and sustainability. The aim of this study is to identify and systematise the legal and institutional mechanisms governing AI development in the European Union and Ukraine, and to assess their alignment with the global sustainable development agenda, based on three hypotheses: (1) the interdisciplinary nature of AI and law; (2) the integration of the UN Sustainable Development Goals into the EU AI Act (Regulation (EU) 2024/1689); and (3) the normative and institutional convergence between Ukraine and the European Union. The methodology applies a triangulated approach combining bibliometric analysis (PRISMA protocol), formal content analysis, and SWOT analysis, ensuring a comprehensive evaluation of legal and managerial aspects of AI governance. The findings show that the EU model balances innovation and accountability through ESG principles, digital ethics, and human-centred governance. Ukraine demonstrates growing alignment with EU law via strategic documents, enhanced digital governance, and participation in international harmonisation programmes. The theoretical contribution lies in conceptualising AI development management as part of a sustainable digital regulation model, reflecting the evolving roles of the state, academia, and business in responsible technology governance. The practical implications include recommendations for developing a national strategy for AI regulation and management, drafting AI legislation harmonised with the EU AI Act, and improving digital governance in the public sector.

Key words

artificial intelligence, AI development management, legal regulation, AI Act, European Union, Ukraine, sustainable development, digital governance, ESG principles, institutional convergence.

Cite as:

Kwilinski, A., & Reznik, O. (2025). Governance of Artificial Intelligence Technologies and Systems in the EU and Ukraine: Legal Foundations and Institutional Mechanisms. *Forum Scientiae Oeconomia*, 13(3), 8–52. https://doi.org/10.23762/FSO_V_OL13_NO3_1

Received: 17 January 2025

Revised: 15 June 2025

Accepted: 28 August 2025



Copyright: © 2025 by the authors. For open-access publication within the terms and conditions of the Creative Commons Attribution (CC BY) licence (<https://creativecommons.org/licenses/by/4.0/>).

Introduction

The first conceptual foundations of artificial intelligence (AI) were established in the mid-twentieth century. A pivotal contribution came from Norbert Wiener (1948), whose work in cybernetics explored the mechanisms of control and communication in living organisms and technical systems. An equally significant milestone was A. M. Turing's (1950) publication proposing the so-called Turing Test as a method for assessing a machine's ability to exhibit intelligent behaviour. The term "artificial intelligence" was formally introduced by John McCarthy during the renowned Dartmouth Conference in 1956 (McCarthy et al., 1955), which is widely regarded as the point of origin of AI as an independent scientific discipline.

From its inception, AI was viewed not merely as a technological innovation but also as a phenomenon requiring institutional and legal governance. The management of AI development, its regulatory foundations, and its institutional design have therefore become integral components of discussions concerning the future trajectory of intelligent systems. The growing academic and policy interest in AI regulation and governance displays exponential dynamics, as evidenced by bibliometric data from leading international databases.

Contemporary scholarship conceptualises AI as a multidisciplinary phenomenon that integrates technical, economic, managerial, legal, ethical, and social dimensions, while also encompassing philosophical and cultural aspects. The present study adopts this interdisciplinary perspective, focusing on the European Union and Ukraine in the context of their European integration. This focus enables the identification of the institutional and legal specificities of AI development management in the process of convergence with the European Union's regulatory framework.

The relevance of this analysis is further reinforced by the wartime context. Since 2014, Ukraine has faced a military conflict triggered by Russian aggression, escalating into a full-scale invasion in 2022. Although such circumstances are profoundly destructive, they have historically acted as catalysts for accelerated scientific and technological advancement and as bifurcation points for systemic transformation. For instance, the First World War spurred developments in aviation, radio communications, and chemical production, while the Second World War stimulated the emergence of the first electronic computing machines (ENIAC, Colossus), nuclear energy, radar systems, and jet propulsion technologies.

The impact of wars and crises on the dynamics of scientific and technological development has been consistently examined by numerous scholars. Kondratiev (1925), within the framework of his long-wave theory, argued that wars and social upheavals act as triggers for transitions to new technological paradigms. Later, de Solla Price (1951), applying quantitative methods, demonstrated the dual effect of armed conflicts: they simultaneously stimulate the emergence of new research directions while inflicting significant losses. Mumford (1970), in developing the philosophy of technology, viewed war as a formative source of the "megamachine" – complex technological and organisational systems. In turn, Glaz'ev (1993), adapting Kondratiev's ideas to modern conditions, showed that military conflicts and global crises accelerate the diffusion of innovations and the shift of technological paradigms.

At the same time, the literature emphasises the reverse relationship: scientific and technological progress itself can radically transform the nature and methods of warfare. As early as the mid-twentieth century, Hamilton and Strausz-Hupé (1952) noted that the character of contemporary wars is largely determined by emerging technological capabilities. In subsequent decades, this topic received further attention. V. Nikitenko (2024) examines the philosophical foundations of how military actions shape social processes and technological development; Chkhikvishvili and Beridze (2024) analyse the role of technological factors in the dynamics of international conflicts; and Hasanov et al. (2024) forecast transformations in military practices under the influence of artificial intelligence, biotechnology, and nanotechnology.

Military conflicts – including those in Ukraine – although occasionally stimulating certain domains of scientific and technological advancement, are frequently accompanied by significant

constraints in academic and applied research. First, during active hostilities, a considerable number of developments become classified or confidential, limiting open knowledge exchange and access to primary data. Second, the destruction of research infrastructure, the forced migration of scientific personnel, the reallocation of public funds towards the military-industrial complex, and the suspension of civilian projects all contribute to the fragmentation of the scientific landscape. Third, heightened national security concerns and stricter secrecy regimes often restrict the dissemination of results that would otherwise be publicly available in peacetime. Collectively, these factors create asymmetries in scientific communication and hinder international cooperation – particularly in high-tech fields such as artificial intelligence – while also contributing to distortions in the information circulating within open academic and expert communities.

At the current stage, the legal regulation of artificial intelligence within the European Union is primarily based on Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024 laying down harmonised rules on artificial intelligence (Artificial Intelligence Act) (European Union, 2024). This document, representing the first comprehensive attempt to institutionalise AI governance in the EU, aims to establish a normative framework that ensures safety, transparency, and the protection of fundamental rights in the design and deployment of AI systems. In this context, the strategic guiding principle for AI development – both within the European Union and in Ukraine – is the concept of sustainable development, enshrined in the United Nations Sustainable Development Goals (SDGs).

Given the transformative potential of AI across diverse domains – including the economy, environment, healthcare, education, governance, and social policy – the governance of AI requires a systemic and holistic approach aimed at achieving all 17 Sustainable Development Goals (SDGs) without exception. Each of these goals is affected by AI either as an instrument of implementation or as a source of emerging challenges and risks. In this sense, AI development cannot be viewed in isolation from the broader global agenda, in which justice, inclusiveness, accountability, and long-term sustainability serve as defining parameters. Thus, effective AI development management entails not only regulatory and institutional support but also the deep integration of sustainability principles into strategic and operational decision-making processes.

The mathematical foundations underlying the functioning of AI systems began to take shape in the 1940s and 1950s, with the emergence of early concepts in algorithm theory, information theory, and artificial neural networks. However, it was during the 1960s–1980s that these ideas underwent systematic development. This period saw the establishment of key directions such as machine learning algorithms, optimisation methods, probabilistic models, and computational mathematics. The limited computational power available at the time significantly constrained the practical realisation of these concepts, resulting in their gradual implementation. Even today, the performance of traditional supercomputers is approaching its efficiency limits, prompting the scientific community to explore fundamentally new paradigms. Among these, the quantum computing model, based on the principles of quantum superposition and entanglement, occupies a particularly prominent place.

In contemporary conditions, artificial intelligence has moved far beyond specialised problem-solving and has become an integral component of digital infrastructure, embedded within the socio-economic fabric of modern society. With the proliferation of the internet and digital technologies, AI systems now permeate almost every sphere of human activity – from communication and medicine to transport, finance, education, and public administration. Their influence manifests both directly – through intelligent services and decision-making algorithms – and indirectly, through smart devices, automated processes, and adaptive control systems capable of responding to user behaviour and preferences. This pervasive integration of AI gives rise to a new ontology of human–technology interaction, in which AI not only performs instrumental functions but also exerts an influence on human development, value formation, and social structures. Consequently, AI is emerging as an active agent in shaping human behaviour and development rather than merely serving as an auxiliary

tool. This evolution necessitates a reconceptualisation of AI's role from both technical and normative–ethical perspectives, emphasising responsibility, transparency, and accountability.

It is important to note that the present study does not claim to provide an exhaustive resolution of the complex issues addressed. Its purpose is to offer an analytical overview and systematisation of the material, positioning this work as an intermediate academic stage that lays the groundwork for further inquiry. The findings can serve as a foundation for both scholarly debate and practical applications, particularly in advancing AI technologies and developing the legal and institutional mechanisms required for their effective and ethical regulation.

This study follows a clearly structured framework consistent with contemporary academic standards. The Introduction establishes the relevance of the topic, outlines the research context, and defines the study's objectives. The Literature Review analyses key academic sources addressing the legal, institutional, and ethical dimensions of artificial intelligence regulation in the European Union and Ukraine. Based on the identified research gaps, the purpose and hypotheses of the study are formulated. The Methodology section presents a combined research framework incorporating bibliometric analysis (according to the PRISMA protocol), formal content analysis of the AI Act in the context of the United Nations Sustainable Development Goals, and a SWOT analysis of Ukraine's legal and institutional framework. The Results section provides empirical evidence and analytical findings confirming the interdisciplinary nature of AI and law research, the normative integration of the Sustainable Development Goals into the structure of the AI Act, and the institutional convergence of Ukraine with the European Union's legal system. The Discussion interprets these results within the broader context of sustainable digital governance, ESG principles, and ongoing processes of legal convergence. Conclusions section summarises the main findings, highlights the theoretical and practical implications, and outlines promising directions for further research in the field of regulation and management of artificial intelligence technologies.

1. Literature review

The rapid advancement of AI technologies has generated a significant surge of interest within the academic community across multiple disciplinary domains – from computer science and law to philosophy, ethics, and public administration. Particular attention is devoted to the development and implementation of both individual AI technologies and complex AI systems, as well as to the formation of effective mechanisms for managing their development.

Given AI's transformative potential, especially in the context of the digital transformation of public administration and international integration, there is an increasing need to systematise existing academic approaches and critically assess the current state of scholarly research. Within this framework, special emphasis is placed on the legal foundations of AI regulation, the institutional mechanisms governing its development, and the distinctive features of their formation under conditions of European integration.

This literature review therefore examines the conceptual underpinnings of artificial intelligence, analyses key academic publications concerning the legal and institutional dimensions of AI governance in the European Union and Ukraine, and identifies major research gaps. The section concludes with the articulation of the study's objective and the formulation of its guiding hypotheses.

1.1 Artificial Intelligence Through the Lens of Scientific Disciplines

Modern AI technologies have penetrated virtually every sphere of human activity, exerting both direct and indirect influence – through digital services, infrastructural solutions, and automated processes. Their rapid proliferation is largely driven by the exponential pace of technological progress, manifested through digitalisation, informatization, robotisation, and automation – all aimed at optimising production, managerial, and social processes. Under these conditions, AI functions not merely as a tool for enhancing efficiency in specific sectors, but as a catalyst for the profound transformation of social and institutional structures.

A key role in the development and large-scale deployment of AI technologies and systems is played by major transnational corporations – Google, Amazon, Apple, Meta, and Microsoft – as well as by next-generation research and technology companies such as OpenAI, Anthropic, XAI, Cohere, and Hugging Face. Their activities not only define the architecture of the global AI market and set the standards for its application but also exert a direct impact on the sphere of governance, contributing to the formation of institutional mechanisms and legal-regulatory approaches to AI oversight. In the Asian market, an analogous role is performed by leading Chinese corporations – DeepSeek, Baidu, Alibaba, SenseTime, Moonshot AI, and Baichuan AI – which are actively developing proprietary large language models and applied AI solutions comparable in sophistication to their Western counterparts. This dynamic further underscores the growing relevance of regulation and control over the development and use of AI technologies.

The contemporary AI industry demonstrates not only a high rate of technological advancement but also increasing concern regarding the governance of its development. Within academic and policy discourse, issues of developer accountability, algorithmic transparency, protection of human rights and freedoms, and adherence to ethical principles in AI design and deployment are being articulated with growing clarity. As the quantitative growth of research output and applied innovations enters an exponential phase, the interaction between human and artificial intelligence is becoming increasingly institutionalised – encompassing regulatory mechanisms at both national and international levels.

Under these conditions, the formation of an optimal model for artificial intelligence (AI) development acquires particular significance. Such a model must be aligned with the strategy of sustainable development and integrated into the implementation of the United Nations Sustainable Development Goals (SDGs). This approach enables the maintenance of a balanced relationship between technological innovation, legal regulation, and social responsibility, while ensuring the long-term sustainability and equity of digital transformation processes.

An analysis of publication activity on the topic of “artificial intelligence,” based on data indexed in the Scopus database, revealed a total of 4,728,583 documents. The leading positions are held by China (1,109,339 publications) and the United States (881,005 publications). However, when the European Union is considered as a single research entity, it ranks first, with a cumulative total of 1,531,064 publications. Collectively, the EU, China, and the United States account for more than half of all publications, underscoring their dominant role in the global research landscape on artificial intelligence. When EU member states are considered individually, eleven of them rank among the top thirty countries by publication volume: Germany, France, Italy, Spain, the Netherlands, Poland, Austria, Sweden, Greece, Portugal, and Belgium (Figure 1). The search criteria and filters applied in this bibliometric query are detailed in *Appendix A*.

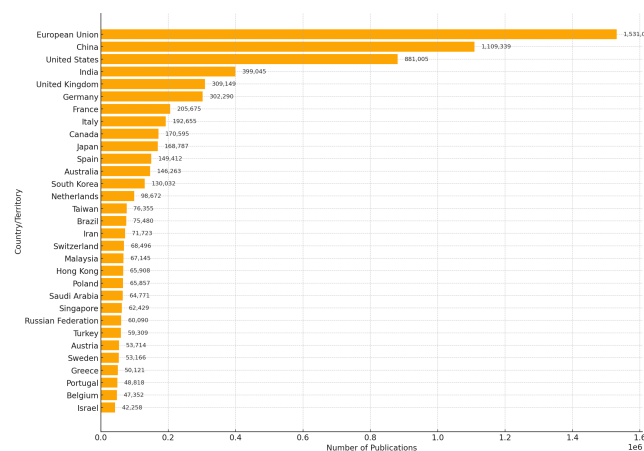


Figure 1. Distribution of publications on artificial intelligence by country/territory (top 30) and the European Union.

Source: Scopus database, authors' own compilation (Appendix A).

Ukraine ranks 53rd globally in terms of the number of publications, with 14,563 articles – a figure that surpasses several EU member states. In particular, Ukraine exceeds Slovakia (57th – 10,572), Slovenia (58th – 10,273), Croatia (63rd – 7,737), Bulgaria (64th – 7,703), Cyprus (66th – 7,110), Luxembourg (67th – 7,082), Estonia (70th – 6,221), Lithuania (72nd – 5,548), Latvia (78th – 3,326), and Malta (89th – 1,876). However, it is important to note that country-level indicators are based on author affiliations, which may exceed the total number of published papers. The aggregate number of affiliations equals 6,150,587, approximately 30% higher than the total number of articles. This discrepancy arises because many publications have multiple co-authors associated with different institutions and countries, meaning that a single article is counted multiple times across national statistics.

The publication dynamics exhibit an exponential growth pattern, which can be approximated using an exponential function. To construct the model, empirical data on the number of AI-related publications for the period 1961–2025 were extracted from the Scopus database according to the applied filters described in Appendix A. The approximation was performed using the least squares method, allowing for the selection of function parameters that best fit the observed values. As a result, the following functional relationship was obtained:

$$y = 3.43 \cdot 10^2 \cdot e^{0.1123 \cdot (x-1960)} - 948.10 \quad (1)$$

where y – number of publications on artificial intelligence in year x ; $3.43 \cdot 10^2$ – scaling constant of the model, defining the initial level of exponential growth; 0.1123 – growth rate coefficient, reflecting the intensity of increase in the number of publications over time; $(x - 1960)$ – time shift parameter, which sets 1960 as the reference point for exponential growth; e – exponential function; -948.10 – adjustment constant of the model, compensating for historical deviations in the data.

The visualisation of the empirical data and the results of the approximation is presented in Figure 2.

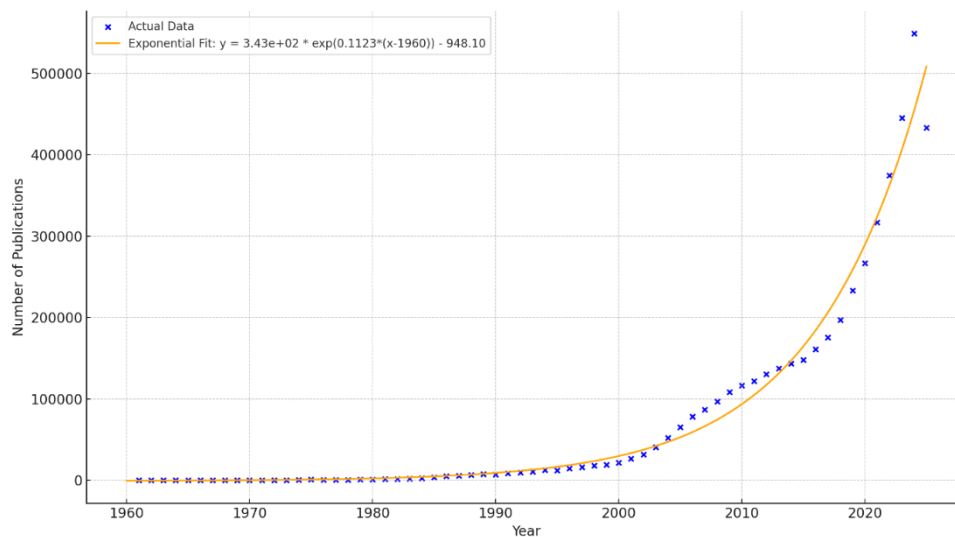


Figure 2. Exponential growth of publications on artificial intelligence (1961–2025) based on Scopus data (2025).

Source: Scopus database, authors' own calculations (Appendix A).

The interpretation of the obtained model indicates that research on artificial intelligence (AI) has entered a phase of accelerated growth, characteristic of exponential processes. This trend is reinforced by the fact that the most highly cited publications in the field of AI are associated with fundamental methodological breakthroughs: ensemble learning algorithms (Breiman, 2001), the development of deep convolutional neural networks (Krizhevsky et al., 2012), the long short-term memory architecture (Hochreiter & Schmidhuber, 1997), specialised networks for image segmentation (Ronneberger et al., 2015), and the systematisation of the deep learning paradigm (LeCun et al., 2015).

These studies have defined the trajectory of modern AI technologies and shaped the research agenda of the past decades.

The widespread dissemination of AI-related publications is confirmed not only by the overall volume of works but also by the diversity of disciplinary domains in which artificial intelligence is developing. According to Scopus, the number of articles attributed to various fields of knowledge substantially exceeds the total number of unique publications, reflecting their interdisciplinary classification and simultaneous attribution to multiple subject areas. The highest concentration of research is observed in computer science (3,262,772 publications), engineering (1,547,710), mathematics (1,321,581), social sciences (382,569), physics and astronomy (321,753), and medicine (321,160). Significant contributions are also made by applied disciplines, including business management, materials science, biotechnology, energy, environmental studies, and the humanities.

Thus, artificial intelligence has evolved into a genuinely interdisciplinary field, integrating fundamental theoretical research with a wide range of practical applications. At the same time, increasing attention within academic discourse is devoted not only to technical and applied dimensions but also to the management of AI development, encompassing institutional mechanisms and legal regulation. The legal dimension, in this regard, becomes an essential precondition for ensuring the sustainable and responsible development of AI, which, in turn, reinforces its exponential growth and defines the long-term trajectory of its integration into social and economic systems.

1.2 Legal Foundations of AI Development Governance in the European Union

For the preliminary analysis, a bibliometric search was conducted in the Scopus database to identify publications related to artificial intelligence and its legal regulation. The resulting dataset (see Appendix B) comprised 67,583 documents, covering a wide range of topics – from legislative frameworks and ethics to governance issues and human rights protection.

To focus specifically on the European Union and Ukraine within the context of European integration processes, a refined search query was developed, incorporating relevant legal categories and geographical indicators (Appendix C). This approach made it possible to identify both the scale and dynamics of research devoted to the legal aspects of managing the development of artificial intelligence technologies in these regions.

The purpose of the publication selection was to identify the scale and dynamics of research devoted to the legal regulation of artificial intelligence in the European Union and Ukraine within the framework of European integration processes. The resulting data enabled the construction of a timeline of publication activity for the period 1986–2024, clearly demonstrating the exponential growth of academic interest in this field (Figure 3).

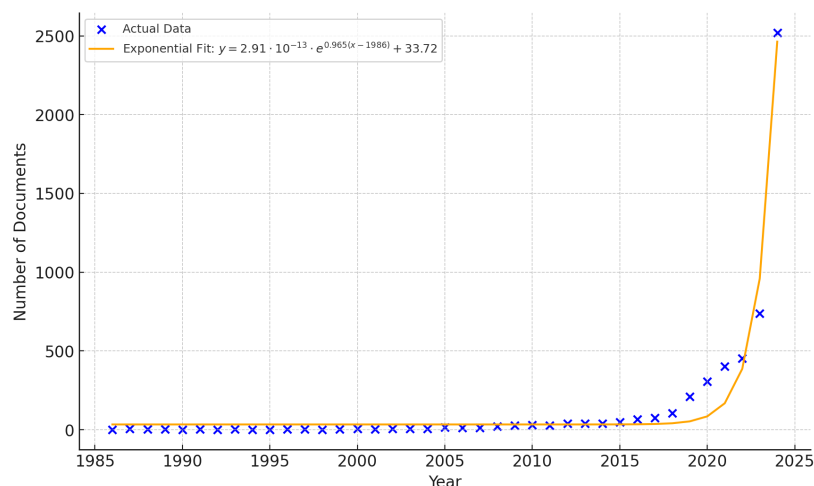


Figure 3. Exponential growth of publications on artificial intelligence and legal regulation in the European Union and Ukraine (1986–2024).

Source: Scopus database, authors' own calculations (Appendix C).

Using the least squares method, an exponential model was developed, with parameters ensuring the closest possible fit to the actual publication statistics. As a result, the following functional relationship was obtained:

$$y = 2.91 \cdot 10^{-13} \cdot e^{0.965(x-1986)} + 33.72 \quad (2)$$

where y represents the number of publications in year x ; 2.91×10^{-13} is the scale coefficient of the model, defining the initial publication level; 0.965 is the growth rate coefficient, reflecting the intensity of publication increase; $(x - 1986)$ denotes the time shift, setting 1986 as the reference point; e represents the exponential function, describing the nonlinear nature of the growth process; and 33.72 is the correction constant, compensating for statistical deviations within the dataset.

Among the European Union member states demonstrating the highest levels of publication activity in the field of artificial intelligence, the top three leaders are Italy, Germany, and Spain. It is particularly noteworthy that following the adoption of Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024, which establishes harmonised rules on artificial intelligence (Artificial Intelligence Act) (European Union, 2024), Italy became the first EU country to enact its own national law governing AI. This refers to “Disposizioni e deleghe al Governo in materia di intelligenza artificiale” (Atto Senato n. 1146, XIX Legislatura), approved by the Senate of the Republic on 20 March 2025 (Senato della Repubblica, 2025). In many other EU states, similar legislative initiatives are currently under development, public consultation, or interministerial coordination, reflecting the overall trend toward the unification of AI regulation in line with pan-European standards.

It should be noted that, despite the 5,240 identified publications, the total number of country affiliations amounts to 7,958, due to the methodological specifics of the Scopus database (Appendix C). As previously mentioned, the same article may be counted for multiple countries because of multi-affiliated authors representing different research institutions and nations. While this leads to a numerical overestimation, it accurately reflects the international cooperation and networked nature of contemporary AI research.

The analysed publications exhibit a distinctly interdisciplinary profile, confirming the broad range of fields addressing the issues of artificial intelligence and its legal regulation. The most active areas include social sciences, computer science, medicine, and engineering, highlighting the dual importance of humanitarian and technological dimensions. Significant contributions also arise from economics and finance, business and management, mathematics, environmental sciences, and decision sciences. Humanities disciplines play an important role, while applied research encompasses energy, biotechnology, healthcare, psychology, and related domains.

Such an interdisciplinary character underscores the complex nature of AI and the need for integration across diverse domains of knowledge to build an effective system for managing and regulating AI development. For greater clarity, the distribution of publications by subject area is illustrated in Figure 4.

Among the most cited publications addressing the legal regulation of artificial intelligence (AI) in the European Union, several key research directions can be identified, forming the foundation of the current academic discourse. These studies reflect not only normative and ethical principles, but also institutional approaches to AI governance, including administrative and legal mechanisms that ensure transparency and accountability of algorithmic systems.

The academic community's primary focus lies in the medical, ethical-legal, and administrative aspects of AI implementation. For instance, He et al. (2019) highlight practical challenges of integrating AI into clinical workflows, emphasising the importance of legal regulation concerning data exchange, privacy, and algorithmic standardisation. Similarly, Gerke et al. (2020) provide a systematic overview of ethical and legal challenges in AI-driven healthcare, including issues of liability, cybersecurity, and personal data protection. Both studies illustrate that the use of AI in

socially sensitive domains is impossible without robust administrative–legal instruments that guarantee oversight, control, and balance between the interests of society, the state, and developers.

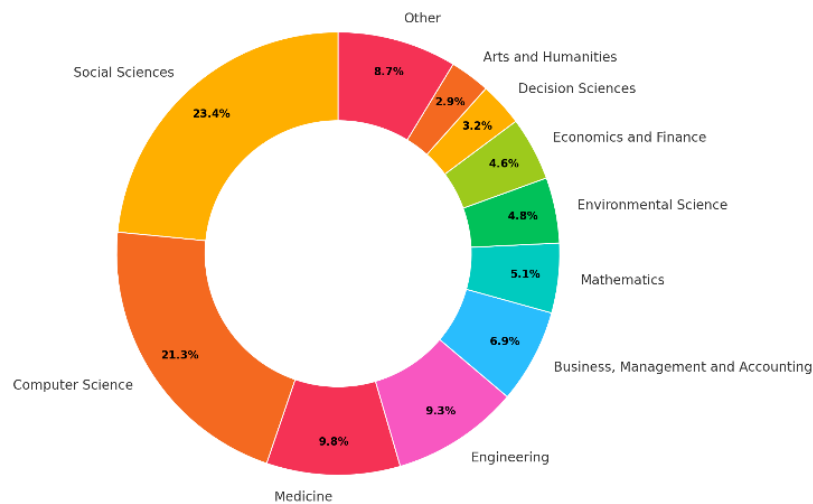


Figure 4. Distribution of publications on artificial intelligence and legal regulation by subject area.

Source: Scopus database, authors' own calculations (Appendix C).

Another crucial research area concerns legal responses to cross-border data exchange and compliance with personal data protection laws. The work of Yang et al. (2020) on federated learning demonstrates that GDPR regulations act as a catalyst for developing decentralised machine learning models, enabling compliance with data protection requirements. In this context, law functions not merely as a regulatory constraint but as a driver of technological innovation, shaping the trajectory of AI's institutionalisation.

Significant attention is also devoted to the political and legal foundations of AI regulation. In their comparative analysis, Cath et al. (2018) examine the strategies of the US, EU, and UK, concluding that despite the EU's institutional activity, it lacks a coherent long-term strategy for AI governance. This underscores the need for a unified administrative–legal framework to ensure policy consistency across the Union.

An additional dimension of the discourse focuses on the regulation of AI-based medical devices. The comparative study by Muehlematter et al. (2021) shows that Europe applies a more flexible but less stringent regulatory model than the US. While this approach facilitates faster innovation adoption, it simultaneously raises risks concerning the quality and safety of medical technologies, highlighting the necessity for legal framework refinement.

A separate research line addresses algorithmic governance in the public sector. The study by Kuziemski and Misuraca (2020) reveals that the use of algorithmic systems in public administration (based on the cases of Canada, Poland, and Finland) can reinforce power asymmetries and create new challenges for democratic institutions. This underlines the need to implement administrative control and oversight mechanisms that could balance the interests of governments, citizens, and technology developers.

Overall, the analysis of the literature on AI governance in the European Union demonstrates that the scholarly debate evolves across multiple domains—from medical and biotechnological applications to data protection and administrative regulation in the public sector. However, existing research remains fragmented, addressing isolated aspects without offering a comprehensive understanding of the interrelations between legal, institutional, and policy dimensions. The lack of systematisation and comparative analysis reveals a significant research gap, which hinders the development of an integrated model of AI regulation aligned with EU-wide priorities and European integration processes.

The AI Act (European Union, 2024) represents the outcome of an institutional consensus on the governance of artificial intelligence (AI) technologies and systems, standing out among the European Union's legal acts for its complex structure and high level of technical detail. Unlike traditional regulations or directives, it operates with technical classifications, risk levels, and certification procedures, making it comparable not to a conventional legal text, but rather to a normative-technical standard. Its interpretation therefore requires not only legal expertise, but also technological literacy, which significantly limits the document's accessibility for a broader audience.

However, the question of how well the provisions of the AI Act align with the Sustainable Development Goals (SDGs) remains open. To test this hypothesis, an extended search was conducted in the Scopus database, using keywords related to the regulation itself, its relationship with the SDGs, and its broader legal-institutional context (Appendix D). The search revealed only a limited number of publications, confirming that this area remains underexplored. The available works focus on specific aspects: the adaptation of the European model in other countries (Yap, 2025); the role of the AI Act in shaping SDG-compatible legal frameworks (Tjokro et al., 2025); comparative studies of regional AI strategies (Tun et al., 2025); and the assessment of AI risks and governance methods (Constantinides et al., 2024; Tjoa et al., 2022).

Meanwhile, studies addressing the relationship between high technology and sustainable development—particularly in the context of AI and digital transformation—highlight a growing interconnection between innovation, sustainability governance, and green economic growth. For instance, research has explored the formation of a culture of sustainable management as the foundation of green economic development (Kwilinski et al., 2025a), the role of digital literacy and ICT competencies in migration processes and human capital development (Kwilinski et al., 2025b), as well as the significance of innovation as a driver of the green economy (Kwilinski et al., 2025c) and the expansion of green financial instruments (Kwilinski et al., 2025d, 2025e).

This discourse is further complemented by empirical studies on public perceptions of AI and its socio-cultural dimensions (Lyulyov et al., 2024), alongside research into institutional and cultural factors influencing green innovation development in various countries (Thirakulwanich et al., 2025). At the intercultural level, special emphasis is placed on educational and value-based aspects of sustainability, as reflected in studies on cross-cultural communication and ethnic diversity in educational environments (Ciuladiene & Walancik, 2022; Ciuladiene et al., 2021), as well as in the monograph on multicultural education strategies (Walancik, 2024).

A separate group of works focuses on strategic management and regional models of sustainable development, identifying the role of cross-border and intercultural cooperation in achieving the SDGs (Dacko-Pikiewicz, 2019). At the macro level, attention is given to the interdependence between digitalisation, energy efficiency, and innovation as key drivers of green growth (Dzwigol et al., 2023, 2024), and to the development of environmental security indicators and risk assessment methodologies employing AI (Kharazishvili & Kwilinski, 2022; Kharazishvili et al., 2025).

An important direction of analysis concerns digital transformation as a key driver of sustainable development (Kwilinski, 2023). It manifests not only in economic efficiency gains, but also in its significant contribution to environmental goals, such as reducing CO₂ emissions (Kwilinski, 2024) and strengthening technological leadership through the relationship between GDP growth and foreign direct investment inflows (Kwilinski, 2025). A number of studies demonstrate that digitalisation is closely linked to the formation of digital governance systems and business models (Kwilinski et al., 2023a), while also enhancing the energy efficiency of EU economies (Kwilinski et al., 2023b).

The continued evolution of this research trend indicates that artificial intelligence is emerging not merely as a technological instrument, but as a core element of the institutional architecture of sustainable development. Analyses of AI's role in sustainable transformation management within the EU (Kwilinski et al., 2024a) and its influence on entrepreneurial transformation in the green economy (Kwilinski et al., 2024b) suggest that technological innovation has become an integral part of ESG

mechanisms, ensuring balanced and responsible growth. These studies reveal the institutional interplay between digital technologies, innovative financial tools, and the SDGs, directly aligning with the normative objectives of the AI Act (European Union, 2024).

At the same time, the cultural and value-based dimension of sustainability is gaining increasing attention in scholarly literature. Recent works emphasise the role of digital culture in advancing the SDGs and shaping the global sustainability agenda (Kwiliński et al., 2024c). Here, digitalisation is conceptualised not only as a technological process, but as a sociocultural phenomenon that integrates sustainability principles into the humanitarian and ethical domains, enriching their normative foundations.

In conclusion, the analysis of existing publications demonstrates that, despite a growing number of studies examining the intersection of the AI Act and the SDGs, a comprehensive approach to evaluating their alignment and institutional coherence is still lacking. This research gap largely stems from the interdisciplinary nature of the regulation itself and the multi-level structure of the SDGs. Therefore, further research is required to develop a systemic understanding of the AI Act's contribution to the implementation of the EU's sustainable development agenda and the global green transition.

1.3 Legal Aspects of AI Development Governance in Ukraine

For the analysis of the legal aspects of AI regulation in Ukraine, a bibliographic search was conducted using the Scopus database and an expanded search strategy that included keywords related to artificial intelligence, legal and institutional frameworks, and a geographical filter for Ukraine. The full search query is presented in Appendix E. The initial search, limited to titles, abstracts, and keywords, identified 262 documents, confirming a growing academic interest in the regulation of AI within the Ukrainian context. For comparison, under equivalent search parameters, the number of publications in the broader European context reaches several thousand, indicating a much higher level of academic activity within EU countries. Hence, while Ukraine's research output remains relatively modest, it demonstrates a clear upward trend, driven by European integration processes and the need to align national legislation with EU regulatory frameworks.

However, this broad dataset proved excessive for the purposes of this study, as a significant proportion of publications addressed AI regulation only indirectly. Therefore, the search was refined to include only titles containing relevant keywords (Appendix F), allowing a focus on the most pertinent works directly related to the intersection of AI and law in Ukraine. The refined selection yielded 12 publications, which formed the basis for further analysis.

The analysis of these publications reveals that the legal regulation and practical application of AI in Ukraine are characterised by a distinctly interdisciplinary approach. A substantial share of studies is concentrated in medicine and healthcare: for example, Osyodlo et al. (2025) discuss the development of an ethical code for AI use in military medical training; Putienko et al. (2025) explore the teaching of ophthalmology during wartime; and Krasnoselskyi et al. (2025) address academic integrity and anti-plagiarism measures in medical research. Further studies examine data standardisation in healthcare systems (Kaduk et al., 2023), the application of AI in obstetrics (Zhylyka et al., 2022), and precision diagnostic technologies in gastroenterology (Stepanov & Zychalo, 2020).

Beyond healthcare, research attention extends to economics, management, energy, and agriculture. Kozlovskyi et al. (2025) investigate AI-based currency exchange forecasting, while Hudima & Kamyshanskyi (2023) analyse the digitalisation and legal regulation of foreign economic policy. Odrekivskyi et al. (2022) examine intelligent systems for competency monitoring in innovation management. In the energy sector, emphasis is placed on interdisciplinary approaches to AI energy supply (Prazian, 2025) and the use of AI in nuclear energy (Golyonko et al., 2025), whereas in agriculture, studies focus on the integration of space technologies into agro-industrial production (Skydan et al., 2019). Collectively, these works span medicine, education, economics, energy, and agriculture, demonstrating the comprehensive and interdisciplinary nature of AI research in Ukraine.

Despite the thematic diversity, a unifying feature of Ukrainian publications is their focus on national challenges – including the consequences of war, the need for reconstruction, and adaptation to EU integration requirements. At the same time, most studies remain sector-specific, addressing individual legal or institutional aspects rather than offering a holistic understanding of AI governance mechanisms, in contrast to the systemic discourse characteristic of EU scholarship.

Thus, although the number of AI-related studies in Ukraine shows a positive growth trend, there remains a significant research gap in works comparing Ukrainian legal frameworks with European standards and exploring harmonisation prospects within the EU legal space. Bridging this gap requires a systemic approach that integrates both legal regulation and institutional governance mechanisms of AI development. A comprehensive comparative analysis of the Ukrainian and EU legal frameworks would make it possible to identify strengths, weaknesses, and priority areas for adaptation, ultimately supporting Ukraine's integration into the unified legal and regulatory architecture of the European Union.

1.4 Research Gaps, Objectives, and Hypotheses of the Present Study

The conducted literature review has revealed several significant research gaps. First, most studies addressing the legal regulation of artificial intelligence (AI) in the European Union and Ukraine are fragmentary in nature. They tend to focus either on individual sectors (such as healthcare, cybersecurity, or labour law) or on specific aspects of regulation (including ethics, data protection, or copyright), without progressing toward a systemic analysis of institutional and legal mechanisms. Second, the issue of comparing Ukraine's national legal frameworks with pan-European standards remains underexplored, which is particularly important in the context of the country's European integration. Third, although the AI Act (European Union, 2024) is a key normative document that directly affects such domains as healthcare, innovation, human rights protection, and institutional development, its connection to the United Nations Sustainable Development Goals (SDGs) has not yet been the subject of a comprehensive academic examination.

Against this background, the aim of this study is to identify and systematise the legal and institutional mechanisms governing the development of AI technologies and systems in the European Union and Ukraine, and to assess their alignment with the global sustainable development agenda, based on the verification of three hypotheses:

- the interdisciplinary nature of legal and AI research;
- the integration of the SDGs within the structure of the AI Act;
- the process of normative and institutional convergence between Ukraine and the EU.

To achieve this aim, the following working hypotheses are proposed:

Hypothesis 1: Research in the field of law and artificial intelligence constitutes a multifaceted interdisciplinary domain, encompassing areas such as data protection, medical law, labour relations, and public administration. It is assumed that this thematic and institutional diversity will be reflected in the distribution of academic publications, thereby confirming the comprehensive nature of AI regulation within the European context.

Hypothesis 2: The substantive provisions of the AI Act directly or indirectly incorporate the priorities of the Sustainable Development Goals, reflected in the alignment of regulatory objectives and instruments with ESG governance principles, digital inclusion, environmental efficiency, and ethical responsibility. It is expected that a detailed analysis of the Act's provisions will reveal a structural correlation between the European model of AI regulation and the global sustainable development agenda.

Hypothesis 3: The Ukrainian legal framework on artificial intelligence demonstrates a trend toward normative and institutional convergence with the EU legal system. This is presumed to manifest through the adaptation of national digital strategies, the harmonisation of legal norms, and the formation of regulatory institutions designed to ensure compatibility with pan-European standards and the principles of the AI Act.

2. Methodology

The study is based on a mixed methodological approach that integrates bibliometric, qualitative, and comparative legal analysis to test the three working hypotheses. The methodological framework combines the PRISMA protocol (PRISMA Guidelines, 2020) for the systematic selection of publications, bibliometric visualisation using VOSviewer (2025), formal content analysis of the Artificial Intelligence Act (AI Act) within the context of the Sustainable Development Goals (SDGs), and a SWOT analysis of Ukraine's legal and institutional framework for artificial intelligence. This multi-level approach ensures both empirical robustness and conceptual depth, integrating quantitative mapping with normative interpretation.

The bibliometric component of the study aims to test Hypothesis 1, which posits that research in the field of law and artificial intelligence constitutes a multifaceted interdisciplinary domain encompassing data protection, medical law, labour relations, and public administration.

The publication search was conducted in accordance with the PRISMA 2020 protocol, as illustrated in Figure 5. Data were extracted from the Scopus database using the search query provided in Appendix C, which included a combination of keywords such as “artificial intelligence,” “law,” “regulation,” “governance,” “policy,” “compliance,” “ethics,” “human rights,” “data protection,” “privacy law”, as well as geographical identifiers related to the European Union and Ukraine.

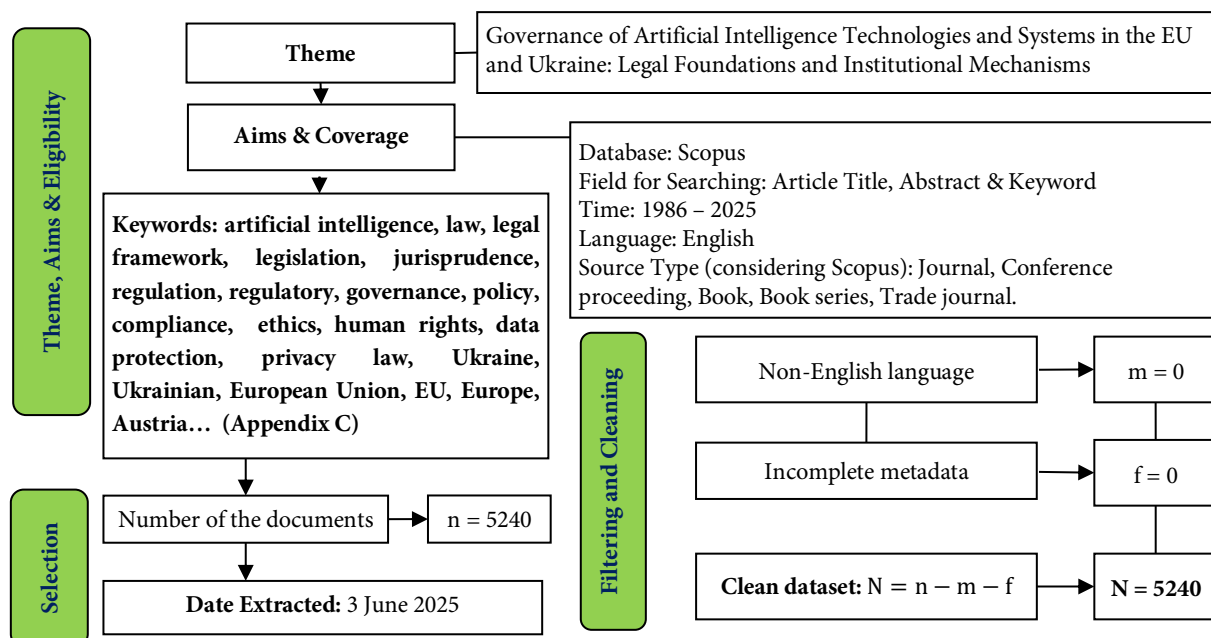


Figure 5. PRISMA Flow Diagram for Identification and Selection of Studies.

Source: Authors' Elaboration Following the PRISMA 2020 Statement (PRISMA Guidelines, 2020).

This query was selected to capture the intersection of legal, regulatory, and ethical dimensions of AI governance, while maintaining a territorial focus on the EU and Ukraine. Such an approach ensures comprehensive coverage of the academic field and provides a balanced representation of research addressing issues of law, policy, and institutional governance.

The resulting dataset comprised 5,240 documents published between 1986 and 2025, all containing English-language metadata (titles, abstracts, and keywords). The dataset was subsequently cleaned to exclude non-English and incomplete records, resulting in a final sample of $N = 5,240$.

To test Hypothesis 1, the study employed VOSviewer software, designed for the construction of network maps and cluster analysis of bibliometric data. The mathematical foundation of this method lies in the creation of a weighted graph, where each element (e.g., author, keyword, or publication) is represented as a node, and the relationships between elements are depicted as edges with assigned weights.

The strength of association between elements i and j is defined by the following formula:

$$S_{ij} = \frac{C_{ij}}{w_i \times w_j} \quad (3)$$

where S_{ij} represents the strength of association between elements i and j ; C_{ij} denotes the number of co-occurrences of these elements; and w_i and w_j correspond to the frequency of occurrence of each element within the dataset.

Thus, the coefficient S_{ij} reflects the normalised intensity of the connection between elements, allowing for consideration not only of the absolute number of their co-occurrences but also of the relative frequency of each within the overall dataset.

The higher the S_{ij} value, the stronger the association between elements – for example, between keywords, authors, or sources – within the analysed thematic domain.

The use of this coefficient ensures the accurate weighting of connections and prevents the analysis from being biased toward the most frequently occurring elements, which is particularly important when constructing clusters and visualising scientific mapping structures in VOSviewer.

Subsequently, the VOS (Visualization of Similarities) algorithm minimises the loss function, expressed as follows:

$$V = \sum_{i < j} S_{ij} (d_{ij} - l_{ij})^2 \quad (4)$$

where V represents the value of the function, reflecting the overall discrepancy between the actual and ideal distances between elements; S_{ij} denotes the strength of association between elements i and j ; d_{ij} is the actual Euclidean distance between nodes on the two-dimensional map; and l_{ij} is the desired (ideal) distance, proportional to the magnitude of the connection S_{ij} .

The purpose of this optimisation function is to position elements (e.g., keywords, authors, or publications) in such a way that the actual distance d_{ij} between them closely corresponds to their logical or semantic proximity l_{ij} , as determined by the strength of their association.

Minimising the function V ensures that the resulting map satisfies the following conditions:

- Elements with high co-occurrence frequency are positioned closer together;
- Elements with low associative strength are positioned further apart;
- The spatial structure of the map reflects the internal organisation of the research field.

This type of visualisation allows for the identification of clusters – groups of elements linked by strong thematic or institutional connections. These clusters can be interpreted as scientific domains, research schools, or subfields emerging within the interdisciplinary space of law and artificial intelligence.

The use of VOSviewer is justified by its ability to combine a rigorous mathematical model of distance optimisation with intuitive data visualisation, making it particularly effective for the exploration of complex interdisciplinary research areas.

Within the framework of the present study, this method enables the empirical validation of the cross-sectoral nature of AI governance research, while also identifying dominant thematic directions and institutional interconnections shaping the European legal model of artificial intelligence.

The second hypothesis aims to assess the degree of integration of the Sustainable Development Goals (SDGs) into the normative content of the European Union Artificial Intelligence Act (2024). To this end, a formal content analysis was conducted by comparing the textual provisions of the Act with the framework of 17 SDGs, adopted by the United Nations General Assembly in 2015 (United Nations, 2015).

Methodologically, the analysis covered all 17 SDGs, since even the absence of a direct correlation between specific provisions of the AI Act and certain goals (e.g., SDG 2 – Zero Hunger or SDG 6 – Clean Water and Sanitation) holds interpretive value, highlighting areas where the Act's influence is

indirect or minimal. This approach provides a comprehensive assessment of the normative alignment between the European model of AI regulation and the universal sustainable development agenda.

For the purposes of this analysis, a correlation matrix was constructed, mapping each article and section of the AI Act against the relevant SDGs and their target indicators. The matrix captures three categories of relationships:

- Explicit link – a direct normative correspondence between provisions of the AI Act and specific SDGs;
- Implicit link – provisions that contribute indirectly to the achievement of SDGs through complementary mechanisms or effects;
- No link – areas where AI regulation exerts no significant influence on the attainment of SDG targets.

Particular attention in this study is given to the Sustainable Development Goals (SDGs) most closely related to technological regulation, ethics, and institutional development, namely:

- SDG 4 – Quality Education;
- SDG 8 – Decent Work and Economic Growth;
- SDG 9 – Industry, Innovation and Infrastructure;
- SDG 12 – Responsible Consumption and Production;
- SDG 13 – Climate Action;
- SDG 16 – Peace, Justice and Strong Institutions;
- SDG 17 – Partnerships for the Goals (particularly in the context of international AI coordination and technology exchange).

This analytical focus made it possible to identify the structural and substantive intersections between the AI Act and the SDG framework, reflecting the European Union's commitment to building an ethical, inclusive, and sustainable model of digital regulation.

The choice of formal content analysis as the main method for assessing this relationship is justified by its ability to provide objective textual correlation between national and supranational legal norms and international regulatory frameworks. This method not only identifies semantic overlaps but also evaluates the degree of institutional integration of sustainability principles into the architecture of European AI regulation. Such an approach ensures a high level of analytical depth and interpretive rigour, which is essential for subsequent comparison with the results of the SWOT analysis of national systems.

To test the third hypothesis, which assumes the existence of a convergence trend between Ukraine's legal and institutional architecture in the field of artificial intelligence (AI) and the regulatory and governance standards of the European Union, a SWOT analysis (Strengths, Weaknesses, Opportunities, Threats) was employed.

The selection of this method is explained by its analytical versatility and its ability to account for the multi-level nature of legal regulation, where internal and external determinants are interrelated. On the one hand, internal factors (such as the legislative framework, institutional practices, and the level of digital governance) define the domestic capacity of the legal system to adapt to European requirements. On the other hand, external factors (including normative pressure from the EU, international cooperation, and the broader political and legal context) shape the direction and pace of harmonisation.

Accordingly, the SWOT framework allows not only to describe the current state of regulation but also to assess the strategic potential for legal convergence between Ukraine and the European Union.

Within the study, four analytical categories were defined:

- Strengths – the existence of national digital transformation strategies, institutionalised AI competence centres, and legislative initiatives aligned with European principles of ethics, transparency, and accountability;

- Weaknesses – fragmented legal acts, limited inter-ministerial coordination, insufficient implementation of ethical and legal AI principles, and constraints in human and financial resources;
- Opportunities – deepening integration with the EU, participation in pan-European digitalisation programmes, adoption of ESG and digital responsibility standards, formation of joint research and innovation clusters, and development of legal cooperation in AI regulation;
- Threats – geopolitical instability, uncertain legal status of certain acts, institutional inertia, regulatory duplication risks, and insufficient enforcement mechanisms.

Methodologically, the SWOT analysis serves as a qualitative framework for the strategic interpretation of institutional adaptation processes, complementing the quantitative methods (bibliometric and content analysis). Its advantage over alternative approaches, such as PESTLE (Political, Economic, Social, Technological, Legal, Environmental) or TOWS (a reverse-logic variant of SWOT), lies in its focus not merely on describing the environment but on evaluating the system's transformative potential. In this study, it enables the assessment of Ukraine's legal readiness for harmonisation with the AI Act, as well as the identification of barriers and growth points in building compatible institutional mechanisms.

The integration of PRISMA-based bibliometric mapping (VOSviewer), formal content analysis, and SWOT evaluation ensures a triangulation of methodological instruments, enhancing the reliability and validity of the findings.

At the first level, the quantitative bibliometric analysis using VOSviewer identifies empirical patterns and thematic clusters in AI law research, reflecting the interdisciplinary structure and institutional complexity of the field.

At the second level, the formal content analysis of the AI Act in comparison with the SDGs establishes the normative and ethical core of the European regulatory model, demonstrating its alignment with principles of sustainability, digital inclusion, and ESG governance.

At the third level, the SWOT analysis of Ukraine's legal framework provides a qualitative interpretation of its institutional dynamics and strategic orientation toward adaptation to European standards.

The integration of these three methodological approaches forms a comprehensive analytical framework, combining quantitative and qualitative perspectives, as well as normative and institutional dimensions, thereby allowing an assessment of the structural and substantive convergence between Ukraine and the European Union in the field of AI governance and regulatory development.

Thus, this multi-level, triangulated methodology enables both the quantitative validation of interdisciplinary trends and the qualitative explanation of governance mechanisms and institutional trajectories that define the evolution of AI legal regulation within the European context.

3. Research results

The integration of three complementary methodological approaches – PRISMA-based bibliometric analysis (VOSviewer), formal content analysis, and SWOT evaluation – made it possible to construct a coherent empirical foundation for testing the proposed hypotheses. This methodological combination ensures data triangulation and enables the institutional and normative convergence processes between Ukraine and the European Union to be examined from multiple analytical perspectives: quantitative, normative-value, and managerial-institutional.

The bibliometric analysis identified the key thematic clusters and evolutionary patterns in legal scholarship on artificial intelligence, revealing the interdisciplinary structure and conceptual diversity of this field. The content analysis of the EU Artificial Intelligence Act (AI Act) in relation to the United Nations Sustainable Development Goals (SDGs) allowed for the identification of the normative core of the European regulatory model, founded on the principles of ethics, accountability, transparency, and sustainability. Meanwhile, the SWOT analysis of Ukraine's national legal framework provided an

EU, its interaction with European law, and issues related to ethics, accountability, and human rights protection.

- Yellow cluster – “Social, Economic and Environmental Dimensions of AI”: It unites such terms as decision support systems, policy, economics, sustainability, climate change, investments, industry 4.0, digitalisation. This cluster highlights the impact of AI on socio-economic processes, environmental governance, and sustainable development, emphasising the link between AI research and the UN Sustainable Development Goals (SDGs).
- Blue cluster – “Health Law and Bioethics”: This group comprises health care, diagnosis, clinical study, telemedicine, medical devices, radiologist, liability, qualitative research. It captures the growing scholarly interest in the legal and ethical aspects of AI use in medicine, including diagnostics, clinical trials, liability for AI-driven decisions, and data protection in healthcare.
- Red cluster – “Biomedical and Public Health Research”: Containing the terms coronavirus infection, pandemics, COVID-19, health care planning, risk factors, cardiovascular disease, cohort study, this cluster reflects the influence of the COVID-19 pandemic on the surge of publications examining the application of AI in medicine, risk prediction, and healthcare system planning.

The next stage in testing Hypothesis 1 involved analysing the temporal structure of publications, illustrating the evolution of the research field in AI law and regulation.

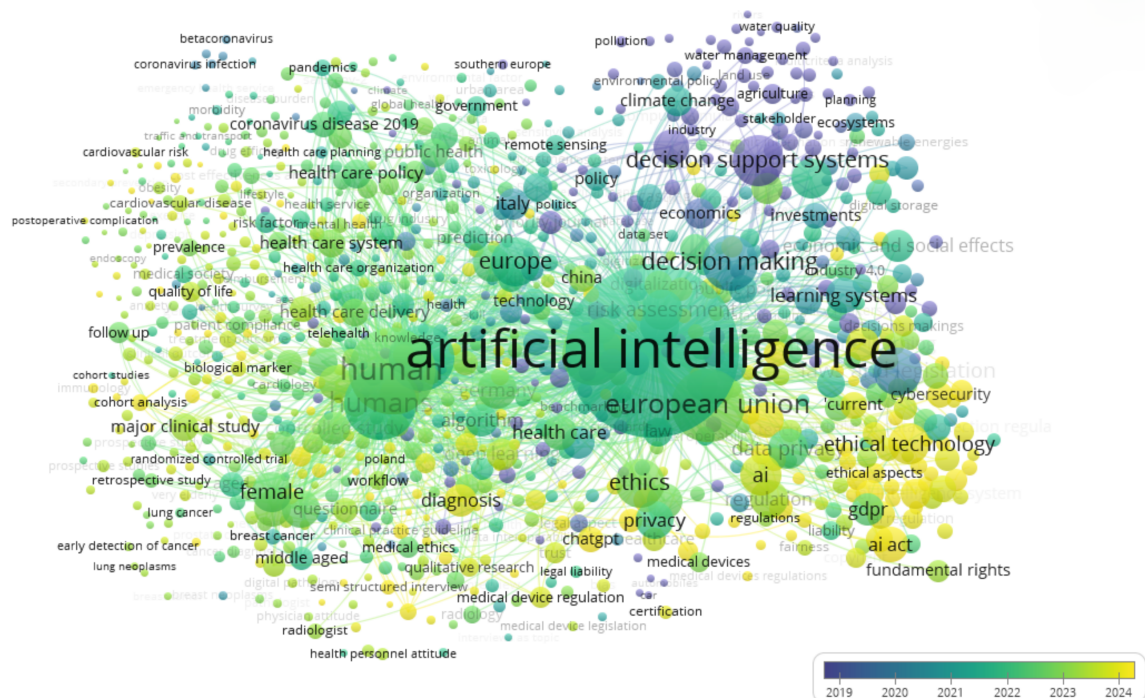


Figure 7. Overlay Visualisation of Term Co-Occurrence in Research on Law and Artificial Intelligence, Created Using Vosviewer Software (Version 1.6.20) Based on Scopus Data for the Period 1986–2025.

The visualisation clearly shows a shift from early technological and biomedical studies to contemporary legal, ethical, and governance-oriented research, thereby confirming the institutionalisation of AI law as an independent and interdisciplinary domain of scientific inquiry.

The green cluster – “AI Law, Ethics and Governance” – includes the terms European Union, regulation, ethics, privacy, fundamental rights, GDPR, AI Act, ethical technology. This cluster remains central and stable throughout the analysed period, showing a steady growth in publications related to AI regulation in the European Union, data protection, and ethical aspects of technology. Since 2020, there has been a marked thematic expansion toward transparency, accountability, and responsible AI, reflecting the institutionalisation of ethical AI governance within the European legal framework.

The yellow cluster – “Social, Economic and Environmental Dimensions of AI” – encompasses terms such as decision support systems, policy, economics, sustainability, climate change, investments, industry 4.0, digitalisation. Its temporal dynamics reveal increased research activity between 2021 and 2023, corresponding to the growing influence of the ESG agenda, digital governance, and the UN Sustainable Development Goals (SDGs). The topics sustainability and digitalisation form a conceptual bridge between legal and technological research domains, underscoring the integrative nature of AI development and governance.

The blue cluster – “Health Law and Bioethics” – includes health care, diagnosis, clinical study, telemedicine, medical devices, radiologist, liability, qualitative research. This cluster dominated in earlier periods (prior to 2020), reflecting the initial research focus on AI applications in medicine, diagnostics, and healthcare management. Over time, these topics evolved to include the ethical and legal implications of medical AI, such as accountability, patient data protection, and algorithmic transparency.

The purple cluster – “Biomedical and Public Health Research” – contains terms such as coronavirus infection, pandemics, COVID-19, public health, risk factors, health care policy, epidemiology. Its peak activity occurred between 2020 and 2021, when the COVID-19 pandemic triggered a surge of studies examining the use of AI in epidemiological modelling, medical logistics, and risk management. After 2022, this cluster’s activity gradually declined, giving way to a growing focus on normative and ethical dimensions of AI governance.

The temporal map illustrates the dynamic evolution of the research field – from applied and medical studies (2019–2021) toward regulatory and governance-oriented research (2022–2024). This transition confirms that the legal discourse on artificial intelligence has emerged as an outcome of the progressive expansion of interdisciplinary links among law, ethics, technology, and social policy.

This trend supports Hypothesis 1, demonstrating that the legal discourse on AI is developing within a stable interdisciplinary paradigm that integrates technical, legal, and governance dimensions of artificial intelligence.

To further clarify the structure and intensity of thematic directions, a density visualisation analysis was conducted (Figure 8), based on Scopus bibliometric data for the period 1986–2025. The map, created using VOSviewer (version 1.6.20), visualises the frequency of term occurrence and the strength of associative relationships within the corpus of publications on AI regulation. The colour intensity indicates the density of mentions: yellow areas represent regions of highest publication concentration, green areas show moderate activity, and blue areas mark peripheral themes.

The term density map reveals a clearly defined multi-layered structure of the research landscape, where the core area consists of concepts related to the legal, ethical, and institutional dimensions of AI regulation, while the peripheral zones are associated with medical, social, and environmental research directions.

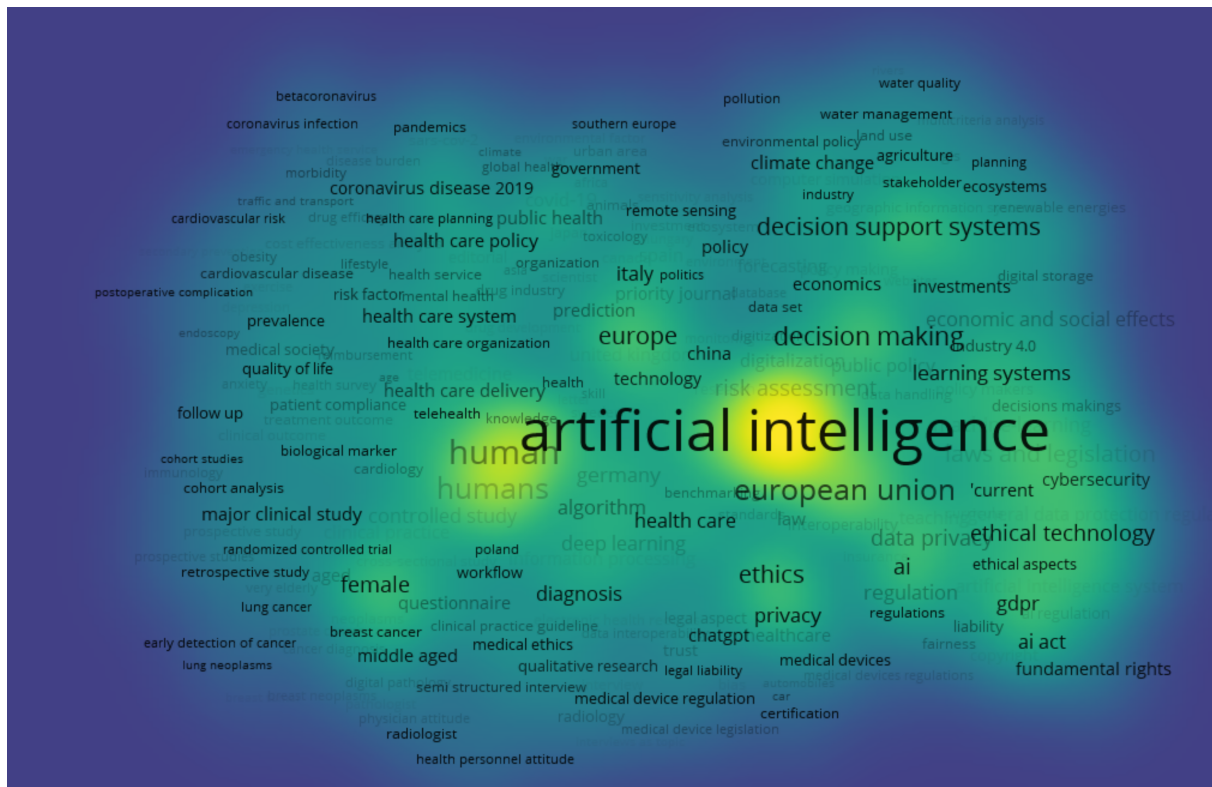


Figure 8. Density Visualisation of Term Co-Occurrence in Research on Law and Artificial Intelligence, Created Using Vosviewer Software (Version 1.6.20) Based on Scopus Data for the Period 1986–2025.

Source: Authors' Compilation Based on Bibliometric Analysis (VOSviewer, 2025).

The central zone (yellow area) includes the terms artificial intelligence, European Union, ethics, regulation, AI Act, GDPR, fundamental rights, and ethical technology. This area forms the normative-ethical core of the academic discourse, reflecting the legal mechanisms of AI regulation, European policy frameworks, and the integration of ethical principles into technology governance.

The intermediate contour (green areas) contains the terms decision making, policy, economics, sustainability, health care, machine learning, and data privacy. This zone concentrates studies that bridge technical, managerial, and socio-economic dimensions of AI, highlighting the interdisciplinary nature of the research field.

The peripheral zones (blue areas) feature terms such as coronavirus infection, public health, telemedicine, climate change, education, employment law, and social effects. These topics demonstrate the expanding scope of AI applications and the emergence of applied research directions – from healthcare and biomedicine to environmental regulation and labour law.

Overall, the visualisation exposes a hierarchical and interconnected structure of AI-law research, where legal and ethical aspects constitute the core, and technical and applied themes form the surrounding field of interdisciplinary interactions.

The results of the density map analysis confirm that the field of AI law and regulation is characterised by a high level of integration between legal, technological, and social dimensions. The dense core centred around the terms AI regulation, ethics, GDPR, and AI Act illustrates the institutional maturity and stability of the European legal discourse on artificial intelligence. Thus, this visualisation empirically supports Hypothesis 1, demonstrating that the research field of AI law is multilayered, interdisciplinary, and structurally balanced.

To further explore the geographical structure of research activity in AI law and governance, a country co-authorship network was constructed based on Scopus bibliometric data (1986–2025). The visualisation, generated using VOSviewer (version 1.6.20), depicts the intensity of international

scientific collaboration among countries. The size of each node corresponds to the number of publications associated with a given country, while the thickness of the connecting lines indicates the strength of cooperative links (Figure 9).

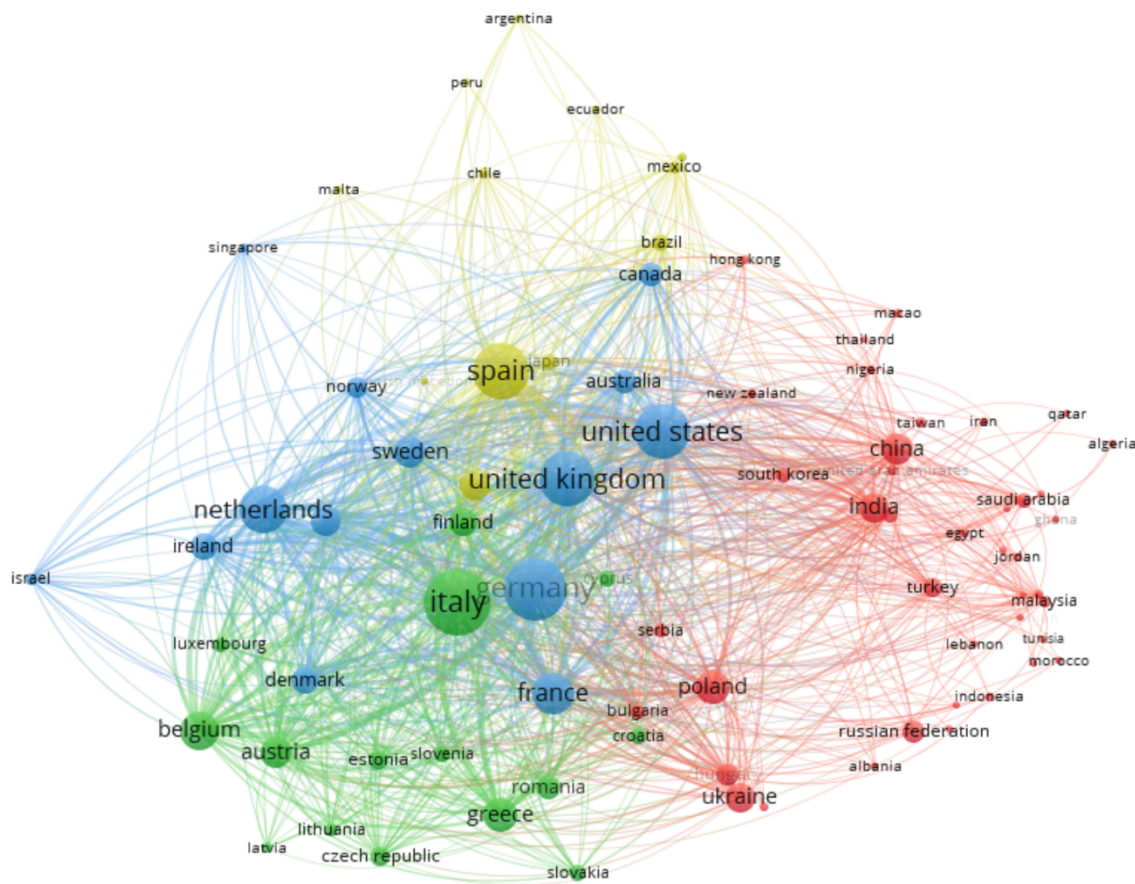


Figure 9. Country Co-Authorship Network in Research on Law and Artificial Intelligence, Created Using Vosviewer Software (Version 1.6.20) Based on Scopus Data for the Period 1986–2025.

Source: Authors' Compilation Based on Bibliometric Analysis (VOSviewer, 2025).

The co-authorship network map illustrates a high degree of international integration within the AI law research landscape and highlights several key hubs of global collaboration:

1. Blue cluster – “Anglo-American Research Core”: Includes United States, United Kingdom, Canada, Australia, Netherlands, Sweden, Norway, Finland, Ireland, and Israel. This cluster represents the leading centre of research on AI law, characterised by a high level of interdisciplinarity, publication activity, and global influence. The US and UK emerge as the most productive and interconnected nodes, shaping international academic standards and discourse.

2. Green cluster – “Continental European Network”: Comprises Germany, Italy, France, Belgium, Austria, Denmark, Greece, Poland, Romania, Czech Republic, Lithuania, and Luxembourg. This cluster reflects the legal and institutional specificity of the EU, marked by intensive collaboration on AI governance, GDPR, AI Act, and digital policy. The most active centres – Germany, Italy, and France – integrate legal and ethical dimensions of AI regulation, reinforcing Europe’s leadership in normative governance.

3. Red cluster – “Asia-Pacific Research Cluster”: Includes China, India, South Korea, Japan, Malaysia, Indonesia, Turkey, Iran, Saudi Arabia, and Qatar. These countries exhibit high publication activity and a technological orientation toward applied AI topics – algorithms, automation, and data

management – though with less normative integration. China and India act as major publication engines, especially after 2020, driving the expansion of AI research in the region.

4. Yellow cluster – “Ibero-Latin Network”: Includes Spain, Portugal, Brazil, Mexico, Argentina, Chile, Ecuador, and Peru. This group represents a growing transatlantic research community, linking European and Latin American approaches to AI ethics, regulation, and sustainable development, thereby broadening the scope of global academic collaboration.

5. Ukraine and Eastern Europe: Ukraine, Poland, and Romania occupy an intermediary position between the green and red clusters, reflecting Ukraine’s increasing integration into the European research ecosystem while maintaining connections with the Asia-Pacific region. This trend empirically confirms Ukraine’s gradual institutional convergence with the EU in the field of AI governance.

The international collaboration network demonstrates that research on AI law and governance is global in scope yet organised around several regional centres – North America, Europe, and Asia. The structure of the network reveals strong intra-European coordination and active Ukrainian participation in the European academic space, providing further empirical support for Hypothesis 1, which posits the interdisciplinary and institutionally integrated nature of AI law research.

The bibliometric analysis conducted for 1986–2025 empirically confirms the interdisciplinary and institutional nature of research on artificial intelligence law within the European academic landscape. The identified clusters – spanning legal, ethical, medical, social, and technological domains – demonstrate that the field of AI regulation functions as a multidimensional and convergent research ecosystem, where normative, technological, and socio-economic components are tightly interlinked.

The temporal and density visualisations trace a clear trajectory: from early technological and biomedical applications to institutionalised legal-ethical frameworks and governance models aligned with European standards. This progression underscores the consolidation of AI law as an independent interdisciplinary field, integrating perspectives from computer science, ethics, data protection, and public administration.

Furthermore, the global co-authorship network reveals a high level of cross-border research integration, positioning Europe as the structural hub connecting the Anglo-American, Asian, and Ibero-Latin research clusters. Ukraine’s embeddedness within this network highlights its increasing institutional alignment with EU legal and governance frameworks, particularly in ethical AI regulation and digital sustainability.

Hence, the findings of the bibliometric analysis provide robust empirical evidence for Hypothesis 1, confirming that AI legal regulation constitutes a multi-level interdisciplinary domain, uniting technological, normative, and ethical dimensions within a coherent European research and governance paradigm.

3.2 Content Analysis of the AI Act and Its Alignment with the UN Sustainable Development Goals

To test Hypothesis 2, a formal content analysis was conducted to examine the extent to which the provisions of the European Union Artificial Intelligence Act (AI Act, Regulation (EU) 2024/1689) reflect and integrate the priorities of the United Nations Sustainable Development Goals (SDGs). The analysis aims to identify the normative convergence between the EU’s regulatory framework for artificial intelligence and the global sustainability agenda, particularly regarding ESG governance, ethical responsibility, and digital inclusiveness.

The hypothesis posits that the AI Act’s structure and principles – including transparency, accountability, safety, fairness, and human oversight – are conceptually and functionally consistent with the sustainable development paradigm, even in areas where the Regulation does not provide explicit sectoral references.

The matrix below (Table 1) presents the correspondence between the provisions of the European Union Artificial Intelligence Act (AI Act, Regulation (EU) 2024/1689) and the 17 United Nations Sustainable Development Goals (SDGs). Each correlation is categorized as either direct, indirect, or absent, depending on the degree to which the regulatory provisions contribute to achieving the

specific SDG objectives. The structure follows the SDG numbering sequence (1–17) to provide systematic coverage of the global sustainability framework.

Table 1. Correlation Matrix between the AI Act and the Sustainable Development Goals.

SDGs	Type of Link	Description of Correlation
1. No Poverty	Indirect	The AI Act contributes to the implementation of certain principles of SDG 1 at the level of economic potential and technological inclusion, but it does not address the social dimensions of poverty eradication. Its impact may therefore be viewed as the creation of infrastructural conditions for sustainable development rather than as a direct instrument of social transformation.
2. Zero Hunger	No Link	The AI Act does not contain explicit provisions addressing food security, sustainable agriculture, or access to nutrition. The Regulation does not directly relate to agricultural innovation or hunger reduction. Its potential contribution to SDG 2 can therefore be viewed as indirect and structural, supporting innovation and sustainability frameworks that may, in the long term, enhance food systems rather than provide immediate regulatory mechanisms for hunger eradication.
3. Good Health and Well-Being	Indirect	The AI Act demonstrates an indirect yet significant correlation with SDG 3 (Good Health and Well-Being). Although the Regulation does not directly govern healthcare systems, several of its provisions—particularly Articles 9, 10 and 14, along with Annex III—establish a regulatory environment that ensures the safety, reliability, and ethical use of AI in medical and health-related contexts. By setting standards for risk management, data quality, and human oversight, the Act contributes to patient safety, responsible innovation, and overall wellbeing. Hence, its contribution to SDG 3 is best described as indirect but foundational, providing the necessary legal infrastructure for sustainable and safe health innovation.
4. Quality Education	Direct	The AI Act demonstrates a clear and direct link with SDG 4 (Quality Education). By introducing the concept of AI literacy (Recital 20) and promoting the development of skills, knowledge sharing, and innovation, the Regulation positions education as a cornerstone of the European digital transition. Its provisions support the creation of an informed and responsible society capable of using AI safely and ethically. Accordingly, the AI Act's contribution to SDG 4 can be regarded as direct and structural, reinforcing inclusive education, lifelong learning, and digital competence as essential dimensions of sustainable development.
5. Gender Equality	Indirect	The AI Act indirectly supports SDG 5 – Gender Equality by embedding principles of non-discrimination, fairness, and human oversight throughout its provisions. Articles 5 and 10 prohibit the use of manipulative or biased AI systems and require the use of representative, high-quality datasets to prevent algorithmic bias. Although gender equality is not explicitly mentioned, the Regulation strengthens the ethical and institutional foundations of equality in AI governance. Hence, its contribution to SDG 5 can be characterised as indirect but legally and ethically substantial, advancing fairness and inclusiveness in the European digital framework.
6. Clean Water and Sanitation	No Link	The AI Act does not contain any direct provisions related to SDG 6. The Regulation does not explicitly address water management, pollution control, or sanitation systems. Its contribution to SDG 6 can therefore be seen as indirect and structural, creating a regulatory environment that could support the future development of sustainable AI solutions in environmental and resource management sectors.
7. Affordable and Clean Energy	Indirect	The AI Act demonstrates an indirect yet meaningful relationship with SDG 7. While the Regulation does not specifically address the energy sector, it recognises the broader environmental and social benefits of artificial intelligence, particularly in enhancing energy efficiency and promoting sustainable technological development. The Act contributes to the creation of a legal and ethical framework that enables the safe and responsible use of AI in energy management and innovation. Its influence is therefore structural rather than sectoral, supporting the long-term transition towards clean and affordable energy through responsible digital transformation.
8. Decent Work and Economic Growth	Direct	The AI Act shows a direct and substantial relationship with SDG 8. It positions artificial intelligence as a driver of innovation, productivity, and competitiveness within the European economy. By fostering a trustworthy digital environment and supporting small and medium-sized enterprises, the Regulation contributes to sustainable economic expansion and job creation. Its framework ensures that technological progress aligns with social responsibility, making the AI Act a cornerstone for inclusive and ethical economic growth in the EU.
9. Industry, Innovation and Infrastructure	Direct	The AI Act demonstrates a strong and direct alignment with SDG 9. It provides a unified regulatory framework for the safe and ethical deployment of artificial intelligence, supporting industrial innovation and the development of trustworthy digital infrastructure. By fostering collaboration between enterprises, research institutions, and regulators, the Act strengthens Europe's capacity for responsible technological leadership. Its contribution to SDG 9 is therefore systemic, shaping the foundations of sustainable industrial transformation and innovation-driven growth within the EU.
10. Reduced Inequalities	Direct	The AI Act shows a direct and socially significant alignment with SDG 10. By prohibiting manipulative and discriminatory AI practices, ensuring transparency, and promoting fairness in algorithmic decision-making, the Regulation strengthens the protection of human rights and social justice. It fosters digital inclusiveness by creating equitable access to technology and innovation across regions and social groups. The AI Act's contribution to SDG 10 is therefore both normative

		and transformative, embedding equality as a foundational principle of the European digital framework.
11. Sustainable Cities and Communities	Indirect	The AI Act demonstrates an indirect but conceptually significant relationship with SDG 1. By defining legal safeguards for the use of AI in public spaces, transport, and critical infrastructure, the Regulation enables the responsible development of smart and sustainable cities. Its emphasis on transparency, safety, and human oversight ensures that digital innovation enhances, rather than compromises, urban inclusiveness and public trust. Hence, the AI Act contributes to SDG 11 by shaping the ethical and institutional foundations of the smart city transformation in Europe.
12. Responsible Consumption and Production	Indirect	The AI Act shows an indirect yet substantial alignment with SDG 12. By embedding transparency, accountability, and ethical design principles into the governance of artificial intelligence, the Regulation supports responsible innovation and sustainable production models. Its provisions help prevent environmental and social harm arising from unregulated technological expansion and ensure that AI development aligns with ESG-oriented practices. Therefore, the AI Act contributes to SDG 12 by establishing a framework for sustainable and accountable digital transformation within the European economy.
13. Climate Action	Indirect	The AI Act demonstrates an indirect yet strategically important link with SDG 13. Although it does not explicitly regulate climate policy, the Regulation promotes the ethical and sustainable use of artificial intelligence in ways that support environmental resilience and energy efficiency. By encouraging innovation in resource optimisation, emissions monitoring, and digital environmental governance, the Act contributes to the broader objectives of the European Green Deal. Its role in relation to SDG 13 is therefore enabling and structural, establishing the legal foundation for AI-driven climate solutions within a sustainable digital transition.
14. Life Below Water	No Link	The AI Act shows no direct link with SDG 14. However, its emphasis on environmental responsibility and ethical technology use provides an indirect framework for the application of AI in marine monitoring and resource protection. By establishing standards for safety, transparency, and accountability, the Regulation enables the development of responsible AI solutions that could support the sustainability of ocean ecosystems in the long term. Its contribution is therefore indirect and enabling, rather than normative or regulatory.
15. Life on Land	Indirect	The AI Act demonstrates an indirect but meaningful connection with SDG 15. While it does not explicitly regulate environmental protection, the Regulation establishes ethical and legal principles that enable the responsible use of AI in land monitoring, biodiversity conservation, and sustainable resource management. Its framework supports the development of “green AI” applications that align with the EU’s ESG agenda, reinforcing the link between technological progress and ecological resilience. Therefore, the AI Act contributes to SDG 15 by providing a governance model for sustainable and ethical environmental innovation.
16. Peace, Justice and Strong Institutions	Direct	The AI Act demonstrates a strong and direct alignment with SDG 16. It establishes a legal framework that reinforces transparency, accountability, and the rule of law in the governance of artificial intelligence. By safeguarding human rights, prohibiting manipulative and discriminatory AI systems, and enhancing institutional oversight, the Regulation strengthens democratic governance in the digital age. The AI Act’s contribution to SDG 16 is therefore structural and foundational, embedding justice and ethical responsibility into Europe’s technological governance model.
17. Partnerships for the Goals	Direct	The AI Act demonstrates a direct and strategic alignment with SDG 17. As the first comprehensive legal framework for artificial intelligence, it sets a global benchmark for responsible technology governance. By promoting international cooperation, knowledge exchange, and harmonisation of regulatory standards, the Regulation strengthens cross-border partnerships between governments, academia, and industry. Its contribution to SDG 17 is therefore institutional and transformative, advancing the EU’s role as a global leader in sustainable and ethical AI governance.

Source: developed by authors.

The correlation matrix presented in Table 1 provides a systematic overview of the degree of alignment between the European Union Artificial Intelligence Act (Regulation (EU) 2024/1689) and the United Nations Sustainable Development Goals (SDGs). The findings indicate that the Act demonstrates a high level of normative and conceptual consistency with the sustainable development framework, confirming the partial to strong integration of ESG principles, ethical accountability, and digital inclusion within the European model of AI governance.

Out of the 17 SDGs:

- 6 goals exhibit a direct correlation (SDGs 4, 8, 9, 10, 16, 17);
- 8 goals show an indirect correlation (SDGs 1, 3, 5, 7, 11, 12, 13, 15);
- 3 goals have no explicit linkage (SDGs 2, 6, 14).

This distribution illustrates that the AI Act primarily contributes to the institutional, ethical, and governance dimensions of sustainable development rather than sectoral or environmental domains.

The Regulation functions as a meta-governance instrument – a legal and ethical foundation enabling sustainability-oriented innovation across various policy sectors.

The AI Act indirectly supports goals related to poverty reduction, health, and gender equality (SDGs 1, 3, 5) primarily through provisions that promote fairness, non-discrimination, and human oversight of AI systems. Its direct contribution to quality education (SDG 4) – through the concept of AI literacy and the promotion of digital competences – demonstrates how the Regulation embeds the principles of empowerment and knowledge dissemination within the digital transition framework. Although no explicit connection was found with zero hunger and clean water and sanitation (SDGs 2 and 6), the Act lays the institutional groundwork for long-term technological inclusion and equality.

The AI Act makes a direct contribution to decent work and economic growth (SDG 8), industry, innovation and infrastructure (SDG 9), and reduced inequalities (SDG 10) by positioning artificial intelligence as a driver of sustainable competitiveness and inclusive growth. It is also indirectly linked to affordable and clean energy (SDG 7) through provisions promoting efficiency and sustainable technological advancement. Collectively, these interlinkages confirm that the AI Act serves as a regulatory catalyst for the digital economy and a just technological transition aligned with ESG principles.

While the Regulation does not contain explicit environmental provisions, its ethical and accountability structure indirectly supports sustainable cities and communities (SDG 11), responsible consumption and production (SDG 12), climate action (SDG 13), and life on land (SDG 15). These relationships highlight the structural contribution of the AI Act – it creates legal conditions for the development of “green” AI solutions consistent with the European Green Deal. A direct correlation with life below water (SDG 14) is absent; however, the Regulation’s focus on safety and transparency may foster future innovations in marine sustainability.

The AI Act directly reinforces the goal of peace, justice and strong institutions (SDG 16) by embedding the principles of transparency, accountability, and human rights protection into the digital governance framework. Furthermore, it contributes to SDG 17 (Partnerships for the Goals) by advancing international regulatory harmonisation and knowledge exchange, thereby positioning the European Union as a global normative leader in ethical and sustainable AI regulation.

Taken together, the results of this analysis show that the AI Act institutionalises the values and objectives of sustainable development within the European model of digital governance. Although the Regulation does not encompass all thematic areas of the SDG agenda, its structure reflects systemic alignment with the social, economic, and institutional pillars of sustainability. This demonstrates that the principles of sustainability are embedded within the normative architecture of the AI Act – not through sectoral mandates, but through an overarching commitment to ethics, equity, and accountability in technology governance.

Thus, the content analysis of Table 1 provides compelling empirical support for Hypothesis 2, demonstrating that the European model of AI regulation is both conceptually and functionally integrated with the UN Sustainable Development Goals, linking digital transformation to the broader paradigm of sustainable and inclusive growth.

3.3 SWOT Analysis of Ukraine’s Legal and Institutional Framework for Artificial Intelligence in the Context of EU Convergence

Hypothesis 3 posits that Ukraine’s legal framework in the field of artificial intelligence demonstrates a trend toward normative and institutional convergence with the European Union’s legislation. This process is expected to manifest through the adaptation of national digital development strategies, the harmonisation of legal norms, and the formation of regulatory institutions aimed at ensuring compatibility with EU standards and the principles established in the Artificial Intelligence Act (Regulation (EU) 2024/1689).

The verification of this hypothesis focuses on identifying the actual degree of institutional and normative convergence between Ukraine and the EU, as well as determining the structural factors

that either facilitate or constrain this process. To achieve this goal, a SWOT analysis is employed, allowing for a comprehensive assessment of the strengths and weaknesses of Ukraine's legal system in the AI domain, alongside the identification of external opportunities and threats shaping its strategic development trajectory.

The use of SWOT analysis is justified by the need not only to diagnose the current state of Ukraine's regulatory and institutional environment but also to evaluate the potential for harmonisation of national legislation with the European model of AI governance. This approach enables the legal framework to be examined within the context of ongoing integration processes, identifying the key directions for its adaptation to the requirements of the AI Act, and aligning it with the principles of digital responsibility, ethics, and sustainability.

In the era of globalisation and Ukraine's active inclusion in the international scientific and technological space, the establishment of an effective legal mechanism for managing the development of artificial intelligence has become increasingly vital. Contemporary global trends indicate that leading innovation centres – the EU, the United States, and China – view AI as a strategic domain of public policy, requiring legal codification, institutional oversight, and ethical control.

Ukraine is likewise engaging in these processes, progressively forming its own regulatory and organisational framework in the field of AI. However, despite the presence of conceptual documents and strategic programmes, the national legal system remains fragmented and requires institutional consolidation. This creates an objective need to examine both the strengths and weaknesses of the Ukrainian legal environment, as well as the external influences that determine the potential and risks of its convergence with EU standards.

Within this context, the SWOT analysis serves as a tool to systematise the key components of Ukraine's regulatory and institutional environment in the AI domain and to evaluate their compatibility with the European model of governance, providing an empirical basis for testing Hypothesis 3.

As previously noted, artificial intelligence represents one of the most transformative technologies of the modern era, with the potential to reshape multiple sectors of social and economic life. Public policy in this domain must ensure the responsible use of AI, balancing innovation and accountability, with the goal of enhancing public service delivery and strengthening democratic governance (Panda et al., 2025). Consequently, effective governance of AI development is becoming a strategic priority of Ukraine's national policy.

The public authorities responsible for managing AI development play a central role in shaping and implementing national policy, establishing regulatory frameworks, and supervising the introduction of innovative technologies. Each of these institutions performs specific functions and exercises distinct powers within the existing legal system, collectively contributing to the sustainable integration of AI across economic sectors and the system of public administration.

At the core of this system stands the Cabinet of Ministers of Ukraine (CMU), which is responsible for implementing state policy, drafting regulatory acts, and coordinating the activities of other executive bodies in the fields of innovation and artificial intelligence. The fundamental principles defining the legal status of the CMU are enshrined in the Constitution of Ukraine (1996). According to Article 113, the Cabinet of Ministers is the highest body in the system of executive power, which grants it a leading role in ensuring public policy across all spheres of social life, including scientific and technological development, digitalisation, innovation, and AI governance.

In this context, the CMU functions as the central coordinating authority of state policy in the AI domain, providing the regulatory, organisational, and financial foundation for the integration of intelligent technologies into the economy, national security, and public administration.

According to Article 116 of the Constitution of Ukraine (1996), the Cabinet of Ministers:

- ensures state sovereignty and economic independence of Ukraine, as well as the implementation of domestic and foreign policy (para. 1);

- conducts financial, investment, tax, educational, scientific, and environmental policy (para. 3);
- takes measures to ensure defence capability and national security (para. 7);
- organises foreign economic activity (para. 8);
- directs and coordinates the activities of ministries and other executive bodies (para. 9).

These functions encompass a wide range of responsibilities relevant to the Cabinet's role in AI development and governance. Accordingly, the government serves as the principal state authority responsible for policy implementation and regulatory support of innovation-driven development, including artificial intelligence.

The second key institution is the Ministry of Digital Transformation of Ukraine (MinCifra), whose legal status is defined in the Regulation on the Ministry of Digital Transformation of Ukraine (Kabinet Ministriv Ukrainy, 2019b). According to this document, the Ministry is responsible for shaping and implementing state policy in the areas of digitalisation, digital economy, digital innovation, robotics, e-governance, and the development of the information society.

In the context of AI technology governance, the Ministry of Digital Transformation of Ukraine (MinCifra) plays a pivotal role. Specifically, it:

- participates in the formulation and implementation of state policy in the field of artificial intelligence, including the development of strategies, programmes, and regulatory acts;
- contributes to the development of AI infrastructure, coordinating the establishment of research and technological platforms;
- plays a key role in international cooperation, facilitating Ukraine's integration into the global digital ecosystem and participation in international initiatives.

Equally significant is the State Service of Special Communications and Information Protection of Ukraine (Derzhspetsvziazok), whose legal foundations are established by the Law of Ukraine "On the State Service of Special Communications and Information Protection of Ukraine" of 23 February 2006, No. 3475-IV. According to the law, Derzhspetsvziazok is a central executive authority responsible for the formulation and implementation of state policy in the fields of special communications, information protection, cybersecurity, and cryptographic data security (Zakon Ukrainy "Pro Derzhavnu sluzhbu spetsialnoho v'iazku ta zakhystu informatsii Ukrainy", 2006).

Derzhspetsvziazok actively integrates AI technologies to enhance the effectiveness of cyber defence, and it participates in international initiatives focused on cyber resilience and innovation. In particular, its representatives took part in the NATO "TIDE Sprint 2025" Conference (Helsinki, Finland), where topics such as cyber threat forecasting, AI applications in intelligence, and information security were discussed (State Service for Special Communications and Information Protection of Ukraine, 2025).

Thus, Derzhspetsvziazok performs a key function in ensuring national cybersecurity, actively integrating AI into information protection systems and contributing to the formation of digital resilience standards.

Beyond the aforementioned bodies, the system of public administration of AI development in Ukraine includes:

- the National Security and Defence Council of Ukraine (NSDC) – coordinates policy in the field of cyber and technological security (Zakon Ukrainy "Pro natsionalnu bezpeku Ukrainy", 2018);
- the Ministry of Education and Science of Ukraine – responsible for advancing research and training qualified personnel in AI;
- the Ministry of Economy of Ukraine – develops innovation policy and supports the digital business sector;
- the Ministry of Defence of Ukraine / General Staff of the Armed Forces – integrates AI technologies into the defence sector, including data analytics and UAV control systems;

- the Security Service of Ukraine (SBU) – counteracts cyber threats and safeguards critical infrastructure;
- the National Agency for Science, Innovation and Informatization – coordinates innovation projects and funds scientific research.

Hence, the system of public administration of AI development in Ukraine is multilevel and complex. The role of public authorities extends beyond setting strategic priorities and developing the legal framework; it also encompasses the practical implementation of tasks related to the development, deployment, and security of AI technologies across various sectors of public life.

Participation of the business sector in building an effective governance system for AI development is becoming increasingly significant in the context of global digitalisation and rapid technological advancement. Enterprises, start-ups, venture funds, industry associations, and other private actors not only develop and implement innovative AI solutions, but also shape the pace, direction, and ethical foundations of AI evolution (Ryan & Stahl, 2021).

Importantly, within the framework of Ukraine's European integration trajectory, the business sector's activity serves as a practical embodiment of European approaches to AI regulation, as enshrined in the AI Act, particularly concerning transparency, accountability, and non-discrimination.

Accordingly, legal regulation of business entities' status and functions in AI governance is of particular relevance. The harmonisation of national legal norms governing private-sector innovation with EU legislation constitutes one of the key indicators of normative convergence and provides additional empirical support for Hypothesis 3.

Given the importance of private-sector participation in AI development governance in Ukraine, it is appropriate to examine the legal status of its key groups.

One of the most important categories of business-sector entities playing a central role in managing AI technologies and systems in Ukraine are legal entities – enterprises. Their innovation potential is largely determined by the scale and depth of AI implementation (Jiang et al., 2024).

This group includes:

- IT companies developing or deploying AI-based solutions;
- industrial enterprises applying AI in logistics, agriculture, and manufacturing;
- research and engineering firms engaged in technological innovation;
- consulting and analytical organisations supporting AI-driven projects.

Among these, IT companies occupy a leading position. Their legal status is governed by a number of normative acts. The general rights and obligations of business entities are defined in the Commercial Code of Ukraine (Commercial Code of Ukraine, 2003) and the Civil Code of Ukraine (Tsyvilnyi kodeks Ukrainy, 2003). Issues of innovation and scientific-technical activity are regulated by the Laws of Ukraine “On Innovation Activity” (Zakon Ukrainy “Pro innovatsiinu diialnist”, 2002) and “On Scientific and Scientific-Technical Activity” (Zakon Ukrainy “Pro naukovu i naukovotekhnichnu diialnist”, 2015). The strategic principles of participation in national AI development are outlined in the Concept for the Development of Artificial Intelligence in Ukraine (Kabinet Ministriv Ukrainy, 2020).

The introduction of such comprehensive approaches into national legislation indicates a progressive convergence between the Ukrainian regulatory model and the European framework, in which digital business is regarded not merely as an economic entity but also as a carrier of ethical and socially responsible practices, fully consistent with the provisions of the AI Act.

The legal status of industrial enterprises applying AI in logistics, agriculture, and manufacturing is determined by the combined effect of the Commercial Code of Ukraine, the Laws of Ukraine “On Innovation Activity” and “On Scientific and Scientific-Technical Activity”, as well as the Concept for the Development of Artificial Intelligence in Ukraine. These enterprises do not develop AI solutions independently but rather integrate them into production processes, thereby creating a sustainable demand for innovation that directly influences the national AI development strategy. Such a model

provides a legal foundation for adapting Ukrainian enterprises to the Industry 4.0 standards and digital transformation agenda defined in the strategic documents of the European Union.

Research-oriented enterprises play a crucial role in the development, testing, and implementation of innovations in the field of AI, in cooperation with universities, IT companies, and industrial organisations. Their activities are governed by the Laws of Ukraine “On Innovation Activity” and “On Scientific and Scientific-Technical Activity”, as well as the Concept for the Development of Artificial Intelligence in Ukraine. These forms of public–private partnership reflect the European model of innovation collaboration, confirming Ukraine’s institutional orientation toward integration with the EU.

The legal status of engineering companies is regulated by the Commercial Code of Ukraine and the Law of Ukraine “On Investment Activity” (Zakon Ukrainy “Pro investytsiinu diialnist”). Within the framework of AI development governance, these companies facilitate the adaptation and integration of AI solutions into production processes and the optimisation of enterprise infrastructure based on intelligent technologies. This aligns with European approaches to technological modernisation and sustainable development.

The legal specifics of consulting and analytical firms supporting AI-related projects are established by the Commercial Code of Ukraine, the Law of Ukraine “On Innovation Activity”, and the Strategy for the Development of Innovation Activity until 2030 (Kabinet Ministriv Ukrainy, 2019a). Although their activities are not governed by a separate law, they operate within the framework of commercial, informational, and innovation legislation. These firms not only provide project support but also shape the legal, strategic, and ethical environment for AI development, directly corresponding to the principles of responsible and transparent AI governance enshrined in the AI Act.

The legal regulation of educational institutions is defined by the Laws of Ukraine “On Education” (Zakon Ukrainy “Pro osvitu”, 2017), “On Higher Education” (Zakon Ukrainy “Pro vyshchu osvitu”, 2014), and “On Scientific and Scientific-Technical Activity” (Zakon Ukrainy “Pro naukovu i naukovo-tekhnichnu diialnist”, 2002), among others. Their role in AI governance and development in Ukraine can be characterised as follows:

- they train specialists capable of developing, implementing, and regulating AI systems;
- they design educational programmes encompassing IT, ethics, governance, and AI regulation (Bećirović & Mattoš, 2024);
- they host research laboratories and AI centres;
- they act as a link between science, business, and the state.

The second category of business-sector entities includes innovation structures – start-ups, technology parks, incubators, accelerators, venture funds, investment platforms, innovation hubs, clusters, and technology transfer centres. Their legal status is governed by the Laws of Ukraine “On Innovation Activity” and “On Scientific and Scientific-Technical Activity”, as well as the Law of Ukraine “On Copyright and Related Rights” (Zakon Ukrainy “Pro avtorske pravo i sumizhni prava”, 2023).

These entities form the organisational and legal infrastructure of innovation development, create favourable conditions for the deployment and commercialisation of AI technologies, and serve as intermediaries between science, business, and government. Their activities contribute to the formation of national innovation ecosystems, fully consistent with European principles embedded in the Digital Europe and Horizon Europe programmes – thus reflecting Ukraine’s institutional convergence with the European Union.

A distinct category of business actors comprises industry associations and alliances, such as IT Ukraine Association, AI HOUSE, and UVCA, which function as platforms for business–government cooperation, the promotion of ethical standards, and the development of self-regulatory mechanisms in the field of AI. These associations help build an effective regulatory environment, participate in the drafting of strategic documents, concepts, and normative acts, and contribute to shaping the national

framework for AI governance. Their activities embody the European principle of multi-stakeholder governance, which is also embedded within the AI Act's institutional design.

Given the rapid advancement of artificial intelligence technologies, effective AI governance requires the participation not only of public authorities and the business sector but also of civil society and the academic and educational community.

Civil society organisations, research institutions, and educational establishments play a crucial role in shaping ethical standards, providing scientific and analytical support, developing innovative solutions, and ensuring capacity building in the field of AI.

The normative foundations of their legal status are defined in the Laws of Ukraine "On Public Associations" (Zakon Ukrainy "Pro hromadski obiednannia", 2012) and "On Scientific and Scientific-Technical Activity" (Zakon Ukrainy "Pro naukovu i naukovo-tekhnichnu diialnist", 2015).

The role of public associations in ensuring AI governance and development in Ukraine manifests in several dimensions:

- they exercise public oversight over the ethical and lawful implementation of AI technologies;
- they serve as experts and stakeholders in drafting AI-related policies, concepts, and legislation;
- they engage in public education and awareness-raising on the opportunities and risks of AI through training, lectures, information campaigns, and social initiatives;
- they promote citizen participation in discussions on the ethical, legal, and social implications of AI development.

Such involvement of civil society reflects the European approach to multi-level governance (multi-stakeholder governance) embedded within the structure of the AI Act, where the participation of public institutions in AI regulatory processes is regarded as a mandatory prerequisite for ensuring transparency and accountability. Thus, the development of the legal status of civil society organisations in Ukraine demonstrates a clear trend toward institutional convergence with the European Union and provides further support for Hypothesis 3.

In today's globalised world, the development of technologies – particularly artificial intelligence systems – is impossible without the active engagement of international organisations, institutions, and partners. International cooperation in the field of AI governance is of critical importance for Ukraine, as it underpins the formation of national policy in this domain and facilitates its integration into global and European digital development processes.

From a legal perspective, the activities of international organisations and partners within Ukraine are regulated by a number of normative acts that establish the foundations for international cooperation and legal harmonisation. These include:

- the Association Agreement between Ukraine and the European Union (Uhoda pro asotsiatsiiu mizh Ukrainoiu, z odniiei storony, ta Yevropeiskym Soiuzom, Yevropeiskym spivtovarystvom z atomnoi enerhii i yikhnimy derzhavamy-chlenamy, z inshoi storony, 2014);
- the Law of Ukraine "On International Treaties of Ukraine" (Zakon Ukrainy "Pro mizhnarodni dohovory Ukrainy", 2004);
- the Law of Ukraine "On the Legal Status of Foreigners and Stateless Persons" (Zakon Ukrainy "Pro pravovyi status inozemtsiv ta osib bez hromadianstva", 2011);
- the Resolution of the Cabinet of Ministers of Ukraine "On the Establishment of a Unified System for Attracting, Using, and Monitoring International Technical Assistance" (Kabinet Ministriv Ukrainy, 2002);
- as well as memoranda and grant agreements with international institutions such as OECD, UNESCO, USAID, and others.

The existence of these legislative instruments provides a legal infrastructure for international cooperation, which is a key element of Ukraine's institutional convergence with the legal and regulatory framework of the European Union and with global mechanisms of AI governance.

A number of international organisations, institutions, and partners are actively engaged in the development of AI technologies and systems in Ukraine. One of the most prominent is the United

Nations Educational, Scientific and Cultural Organization (UNESCO), which promotes the concept of human-centred, ethical, fair, and sustainable AI development that serves human interests, respects human rights, reduces inequality, and contributes to national development (van Norren, 2023). In Ukraine, UNESCO's activities have a significant influence on the ethical, legal, educational, and research environments within which AI platforms and governance frameworks are formed.

Another major international partner of Ukraine is the United States Agency for International Development (USAID), which actively supports digital transformation, innovation development, and technology governance, including artificial intelligence. USAID can be regarded as a key provider of international technical assistance, implementing programmes that directly or indirectly promote AI development in Ukraine, strengthen institutional and human capacities, and foster digitalisation, data governance, and innovation.

The Organisation for Economic Co-operation and Development (OECD) also plays a pivotal role. It developed and adopted the OECD Principles on Artificial Intelligence – the first intergovernmental document defining the ethical, legal, and governance framework for AI development and use. The OECD provides Ukraine with expert and methodological assistance in harmonising digital legislation and designing national AI strategies, particularly in the context of alignment with the EU AI Act.

The activities of UNESCO, USAID, and OECD are primarily directed towards supporting low- and middle-income countries, helping them bridge the technological divide through technology transfer, grant support, knowledge exchange, and professional development (Khan et al., 2024). For Ukraine, this support is of special significance, as it enhances both its scientific and technical potential and the alignment of its digital policy with international and European standards of responsible AI governance.

The international partners discussed above play a crucial role in shaping the contemporary system of AI governance in Ukraine. Their activities aim to:

- develop and implement ethical and legal standards for AI;
- strengthen the institutional and financial capacities for digitalisation and innovation;
- promote the harmonisation of Ukraine's national policies with international principles of responsible, human-centred AI, including the principles of transparency, accountability, sustainability, and non-discrimination.

Thus, it can be concluded that Ukraine's foreign policy and institutional trajectory in the field of artificial intelligence is consistently oriented toward the European model of ethical, responsible, and sustainable digital governance. This is evident both in the content of its legal acts and in the nature of its international partnerships. Such a direction of development provides further empirical confirmation of Hypothesis 3, indicating progressive normative and institutional convergence between Ukraine and the European Union's legal space in the field of AI regulation.

Based on the analysis of the legal status of state authorities, the business sector, academic and educational institutions, and international partners, it is appropriate to proceed to the systematisation of findings in the form of a SWOT analysis (Table 2). The SWOT matrix summarises the strengths and weaknesses, as well as the opportunities and threats for the development of Ukraine's national legal framework in the field of artificial intelligence. This, in turn, enables an assessment of the degree of its alignment with the principles and structure of regulation established by the EU AI Act.

The results of the conducted SWOT analysis indicate that Ukraine's legal system in the field of artificial intelligence regulation is in a stage of active formation, characterised by a combination of significant institutional potential and fragmented normative development.

Among the key strengths are the presence of strategic policy documents (notably, the Concept for the Development of Artificial Intelligence in Ukraine, 2020), a developed institutional infrastructure encompassing state bodies and academic institutions, as well as active participation in international initiatives and alignment with European approaches to ethical AI governance.

Table 2. SWOT Analysis of the Development of Artificial Intelligence Regulation in Ukraine in the Context of Convergence with the European Union Legal Framework.

STRENGTHS	WEAKNESSES
1. Existence of strategic and conceptual frameworks – the Concept for the Development of Artificial Intelligence in Ukraine (2020), as well as strategies for digital transformation and innovation development up to 2030, align with the goals of Digital Europe.	1. Fragmented regulatory framework – the absence of a comprehensive Artificial Intelligence Act; legal regulation remains dispersed across various legislative domains (innovation, science, information law, cybersecurity).
2. Institutional infrastructure – key public authorities such as the Cabinet of Ministers, the Ministry of Digital Transformation, the State Service for Special Communications and Information Protection, the Ministry of Economy and the Ministry of Defence play active roles in AI policy implementation.	2. Insufficient inter-agency coordination – no single national coordinating centre or agency for AI policy exists, which reduces policy coherence and governance efficiency.
3. Active participation in international initiatives and partnerships – cooperation with the EU, UNESCO, OECD, and USAID facilitates integration into global programmes on responsible and ethical AI.	3. Limited human and financial capacity – a shortage of highly qualified AI law and policy experts, and insufficient funding for research centres and higher education programmes.
4. Growing AI business ecosystem – development of IT companies, start-ups, technology parks, venture funds and clusters; active role of associations (AI House, IT Ukraine Association, UVCA) in promoting policy dialogue and ethical standards.	4. Undefined legal status of several actors – the roles and powers of non-governmental and private entities in AI governance remain legally uncertain.
5. Strong role of science and education – universities and academic institutes conduct AI research, design training programmes and establish dedicated AI research centres.	5. Insufficient implementation of ethical and legal principles – transparency, accountability and non-discrimination principles are not yet fully incorporated into national law.
6. Development of cybersecurity and data protection mechanisms – the State Service for Special Communications plays a crucial role, with Ukraine's participation in NATO's TIDE Sprint 2025 and the use of AI for cyber defence.	6. Weak enforcement mechanisms – despite existing conceptual frameworks, control, monitoring and liability mechanisms remain underdeveloped.
OPPORTUNITIES	THREATS
1. Harmonisation with the EU Artificial Intelligence Act (2024) – adoption of common risk-based regulatory principles, transparency, ESG and sustainability standards.	1. Geopolitical instability and ongoing military conflict – diversion of resources, infrastructure damage, and reduced investment in IT and AI sectors.
2. Deeper integration into the European digital ecosystem – participation in Digital Europe, Horizon Europe, and the European AI Alliance, enabling knowledge exchange and technology transfer.	2. Institutional inertia and bureaucratic resistance – slow legislative adaptation and reluctance to reform within public administration.
3. Expansion of international cooperation – access to grants, investments and technical assistance from the EU, OECD, USAID, and UNESCO.	3. Regulatory overlap risks – potential inconsistencies between national and EU legal norms, especially in cybersecurity and data protection.
4. Implementation of ESG and digital responsibility principles – advancing legal frameworks that incorporate sustainability, ethics and social inclusivity.	4. Uncertain legal status of certain policy documents and institutions – many strategies remain declarative, lacking concrete implementation mechanisms.
5. Creation of international research and technological clusters – integration of universities, start-ups and government institutions into transnational AI innovation networks.	5. Brain drain risks – migration of AI specialists and researchers abroad due to economic or security-related factors.
6. Digitalisation of public administration – using AI to enhance transparency, efficiency and accountability in public governance.	6. Insufficient data protection and ethical safeguards – risk of misuse of personal data and algorithmic bias in governance systems.

Source: developed by authors.

At the same time, the weaknesses reveal the absence of a comprehensive legislative framework, insufficient inter-agency coordination, and weak implementation mechanisms for ethical norms. These shortcomings substantially slow down the process of legal convergence with the European Union and underscore the need for institutional strengthening and systemic legislative integration.

The opportunities identified demonstrate that Ukraine possesses a wide potential for integration into the European digital ecosystem through participation in programmes such as Digital Europe and Horizon Europe, as well as through harmonisation with the EU AI Act (2024). The effective realisation of these opportunities would enhance the country's legal resilience, digital ethics, and innovation capacity, consolidating its position within the European framework of responsible technological governance.

The primary threats are associated with external political and economic factors – above all, the ongoing military conflict, institutional inertia, and human resource constraints. Nevertheless, the presence of international support, particularly from organisations such as the OECD, UNESCO, and USAID, mitigates some of these risks and contributes to maintaining Ukraine's Eurointegration trajectory.

Overall, the results of the SWOT analysis confirm Hypothesis 3, which posits that Ukraine's legal and institutional framework in the field of artificial intelligence demonstrates a steady trend toward normative and institutional convergence with the legislative system of the European Union. This convergence is manifested through the adaptation of strategic documents, participation in international partnerships, and the integration of ESG principles and ethical-legal mechanisms consistent with the requirements of the EU AI Act.

3.4 Synthesis of Findings and Confirmation of Research Hypotheses

The integrated application of bibliometric analysis, formal content analysis, and SWOT evaluation has provided comprehensive empirical evidence supporting all three hypotheses formulated within this study.

First, the results of the bibliometric analysis of interdisciplinary publications in the field of artificial intelligence and law have confirmed Hypothesis 1, demonstrating that scholarly activity in this domain indeed forms a cross-sectoral and multidimensional research field. The identified thematic clusters encompass such areas as data protection, medical law, labour relations, and public administration, reflecting the systemic and institutionally integrated nature of AI regulation in the European context.

Second, the findings of the formal content analysis of the European Union Artificial Intelligence Act (Regulation (EU) 2024/1689) have confirmed Hypothesis 2, revealing a clear integration of the United Nations Sustainable Development Goals (SDGs) into the normative architecture of this legal act. The AI Act institutionalises the principles of ethical, inclusive, and sustainable digital governance, aligning its regulatory mechanisms with the ESG paradigm and the global sustainable development agenda.

Third, the conducted SWOT analysis of Ukraine's legal and institutional environment has empirically confirmed Hypothesis 3, demonstrating the progressive convergence of the national AI regulatory system with the European model. The harmonisation of strategic, normative, and institutional components – from the Concept for the Development of Artificial Intelligence in Ukraine (2020) to digital transformation strategies and active cooperation with the EU, OECD, UNESCO, and USAID – provides evidence of Ukraine's consistent movement toward the principles and standards established in the EU AI Act.

Taken together, the results show that Ukraine's approach to AI governance and regulation is evolving in accordance with European norms of responsibility, transparency, and sustainability. This confirms that the national legal system is undergoing a process of normative and institutional alignment with the European model of ethical AI regulation.

Accordingly, all three research hypotheses have been fully validated, providing a robust empirical foundation for further analytical generalisation and the development of strategic policy recommendations aimed at improving Ukraine's national legal framework in line with European and global standards.

4. Discussion

The results of the conducted study confirm the interdisciplinary, normative-institutional, and strategic nature of the processes governing the development of artificial intelligence (AI) in the European Union and Ukraine. The analysis has revealed a sustained trend toward the convergence of legal systems, which is manifested not only in the formal adoption of regulatory approaches, but also in a deeper institutional integration of the principles of responsibility, transparency, and sustainability.

However, the confirmation of all three hypotheses does not preclude the need for a critical reflection on a number of factors that may exert a significant influence on the dynamics and interpretation of the results obtained.

4.1 Global and Technological Factors of Influence

The contemporary stage of artificial intelligence (AI) development is characterised not merely by the acceleration of computational processes, but by a qualitative transition toward new levels of interaction between computational systems and the physical and social world. The increasing speed of computation, approaching its physical limits, creates the preconditions for phenomena whose consequences cannot yet be fully assessed. Whereas in the mid-twentieth century computational velocity was measured in milliseconds, modern quantum and neuromorphic architectures are bringing us closer to regimes in which information processing occurs with near-instantaneous synchronisation—a speed of simultaneity comparable to the ultimate physical constants.

This opens unprecedented prospects, yet simultaneously calls into question the applicability of many existing principles of digital and legal regulation. The concepts of responsibility, causality, and predictability of algorithmic decisions—traditionally forming the foundations of legal systems—may require radical reconsideration. A situation is emerging in which the speed of AI-driven decision-making surpasses human capacities for control and interpretation, producing an “institutional temporal gap” between action and legal response.

At the same time, there is a growing scale and impact of malicious operations employing AI—including cyberattacks, manipulative media campaigns, and harmful software designed to destabilise social systems or undermine critical infrastructure. Contemporary AI tools can generate highly realistic fabrications, falsify data, simulate personal profiles, and even mimic managerial decisions, thereby necessitating not only technical but also legal countermeasures. Hence, the regulation of AI extends beyond the boundaries of national legal orders and becomes an element of global human security.

Under these conditions, the importance of ethical and legal oversight is significantly amplified. Traditional control mechanisms—expert evaluation, certification, and audit—must evolve into dynamic systems of monitoring and legal adaptation capable of responding in real time. This transformation implies the integration of cybersecurity, law, and the philosophy of science into a unified interdisciplinary framework.

4.2 Reconceptualisation of the Principles of AI Governance

The fundamental legal principles currently in force – transparency, accountability, respect for human rights, and non-discrimination – emerged in an era when technologies were linear, deterministic, and manageable. However, the transition to systems based on deep learning, self-learning, and quantum computation is transforming the very nature of controllability.

This shift generates the need for a new generation of digital-law principles, capable of accounting not only for causal relationships, but also for probabilistic, stochastic, and systemic interdependencies. Among such emerging principles, the following may be identified:

- the principle of probabilistic accountability, which recognises the statistical degree of AI participation in decision-making;
- the principle of cognitive symmetry, requiring that humans and machines be afforded comparable capacities to comprehend the logic of algorithmic actions;
- the principle of systemic adaptability, obliging the legal system to evolve in synchrony with technological advancement.

Such a transformation of the legal foundations necessitates a reconsideration of existing instruments, including the EU Artificial Intelligence Act, which may require further expansion to encompass the regulation of quantum computing, generative models, and autonomous systems. Consequently, any assertion of stability within the European regulatory model must be understood in the context of its inherent dynamic evolution.

4.3 Ethical and Civilisational Dimensions

Artificial intelligence is becoming not merely an instrument, but an element of an emerging anthropo-technological synthesis, in which the boundary between human and machine is progressively blurred. This convergence gives rise to profound philosophical and legal dilemmas concerning personhood, identity, and accountability. Questions regarding the rights of AI and its status as a subject or object of law remain unresolved and continue to challenge the conceptual limits of contemporary jurisprudence.

Amid the rapid development of autonomous systems, there arises a pressing need for meta-legal mechanisms—frameworks capable of regulating not only the application but also the very feasibility of creating certain categories of technologies. This issue becomes particularly acute in the military domain, where the integration of AI into weapons control systems raises the spectre of losing human oversight over decisions that directly concern life and death.

These challenges are further exacerbated by geopolitical instability, economic polarisation, and informational vulnerability. Taken together, these dynamics create the preconditions for the emergence of a new ethical contract of humanity—one that must delineate the boundaries of the permissible in the use and creation of artificial intelligence.

4.4 The Impact of Global Factors on the Interpretation of Results

The confirmation of all three research hypotheses must be interpreted through the lens of broader global contexts, encompassing:

- the military-political dimension, reflecting the role of AI in ensuring security and maintaining strategic balance;
- the technological dimension, associated with the quantum leap in computational capacity;
- the economic and ecological dimension, expressing the impact of digitalisation on sustainable development.

Each of these factors has the potential to reshape the interpretation of empirical findings. For instance, the dynamics of Ukraine's convergence with the European Union in the legal regulation of AI may accelerate not solely as a result of institutional European integration, but also under the pressure of military exigencies and technological imperatives.

Moreover, the ongoing processes of global standardisation, led by the European Union, the United States, and China, may give rise to asymmetric harmonisation, in which partner countries are compelled to adapt their legislation at a faster pace than their internal institutional capacities can sustain. This creates the risk of formal rather than substantive convergence, where harmonisation is reduced to the replication of norms without a genuine integration of ethical and value-based foundations.

4.5 Research Limitations

Despite the comprehensive and multi-layered design of this study, several limitations must be acknowledged. First, the bibliometric data are inherently dependent on the coverage and structure of the Scopus database, which may introduce a selection bias favouring English-language publications and Western research institutions. Second, the formal content analysis of the EU Artificial Intelligence Act (AI Act) is confined to a textual comparison and does not encompass the broader interpretative corpus emerging from European judicial and administrative practice. Third, the SWOT analysis of Ukraine's legal system reflects the state of affairs as of 2025, whereas regulatory developments are evolving rapidly, which may affect the short-term validity of some conclusions. Fourth, the study does not consider informal and non-institutional mechanisms of regulation, such as sectoral agreements, corporate ethics codes, and self-regulatory protocols, which also play a growing role in shaping the practical governance of artificial intelligence.

4.6 Prospects for Further Research

Future research may be directed towards several key areas:

- the development of a predictive legal methodology capable of anticipating the consequences of technological innovation before their materialisation;

- the analysis of legal regimes governing quantum AI and the unique risks associated with such systems;
- the formulation of ethical standards for generative models and autonomous systems;
- a comparative examination of national AI regulatory strategies across Asia, Europe, and North America;
- the study of AI's influence on the transformation of the very concepts of sovereignty and public governance.

Thus, the discussion confirms that the regulation of artificial intelligence requires not merely an update of existing legal frameworks, but a reconsideration of the fundamental principles of law in light of new physical and technological realities. Contemporary challenges – ranging from quantum acceleration of computation to ethical threats posed by AI-enabled sabotage – call for a comprehensive and interdisciplinary response, uniting international law, science, and philosophy.

At the same time, the present study demonstrates that Ukraine is advancing towards normative and institutional convergence with the European Union, while the broader global processes of digitalisation and computational expansion are shaping new horizons for legal evolution and the future architecture of technological governance.

Conclusions

The present study has undertaken a systematic analysis of the legal and institutional mechanisms governing the development of artificial intelligence (AI) in the European Union and Ukraine, viewed through the lens of the global sustainable development agenda.

By employing a triangulated methodological framework – combining PRISMA-based bibliometric analysis, formal content analysis, and SWOT assessment – the research achieved a multidimensional perspective that enabled the empirical confirmation of all three proposed hypotheses.

Firstly, the bibliometric analysis empirically confirmed the interdisciplinary nature of AI and law research. The formation of four stable clusters – AI Law, Ethics and Governance; Social and Environmental Dimensions of AI; Medicine and Bioethics; and Public Administration and Security – demonstrates the institutionalisation of AI law as an independent field of inquiry. This finding validates Hypothesis 1, showing that the regulation of artificial intelligence in the European context is complex and cross-sectoral, encompassing legal, ethical, managerial, and technological dimensions.

Secondly, the results of the formal content analysis confirmed the structural integration of the United Nations Sustainable Development Goals (SDGs) into the architecture of the AI Act (Regulation (EU) 2024/1689). The provisions of the Act correlate directly or indirectly with SDGs 4, 8, 9, 12, 13, 16, and 17, reflecting the transformation of the European regulatory model towards sustainable, ethical, and accountable governance. The European Union thereby advances a unique normative paradigm in which digital regulation is conceived not as a constraint, but as an instrument for promoting ESG principles, digital inclusion, and social justice. This fully confirms Hypothesis 2.

Thirdly, the SWOT analysis of Ukraine's legal and institutional framework revealed consistent signs of normative and managerial convergence with the European Union. Among the key strengths are the existence of strategic documents, a developed institutional infrastructure, and participation in international initiatives. Weaknesses include the fragmentation of legislation and insufficient inter-agency coordination. Nevertheless, significant opportunities arise through harmonisation with the AI Act, deeper integration into EU digital programmes, and the creation of joint research clusters. Despite threats posed by ongoing war and institutional inertia, Ukraine's strategic trajectory of legal transformation remains aligned with the European course. These findings confirm Hypothesis 3, affirming the progressive convergence of Ukrainian and European legal systems in the field of AI regulation.

The empirical results are further substantiated by the institutional architecture established in Ukraine to manage AI development. Governance in this domain emerges as the outcome of coordinated interaction among multiple actors at national and international levels.

At the national level, key roles are played by governmental bodies responsible for digitalisation and innovation policy, which design strategic frameworks and legislative instruments defining the direction of AI deployment.

The business sector acts as the main driver of technological progress, investing in research, development, and implementation of AI solutions, while fostering employment and digital competence.

Civil society, academic, and educational institutions provide research, ethical, and educational support, preparing skilled professionals and shaping standards for responsible AI use.

Meanwhile, international organisations and partners – including UNESCO, USAID, and the OECD – provide financial, technical, and institutional assistance, facilitating the harmonisation of standards and integration of Ukraine into the global ecosystem of ethical and sustainable AI.

The interaction among these actors constitutes an integrated governance ecosystem, combining legal, ethical, and innovation mechanisms that ensure the sustainable development of AI technologies in Ukraine.

Taken together, the findings demonstrate that the regulation of artificial intelligence transcends a narrow legal discourse and has become a central element in the transformation of public governance, economic systems, and international law. Processes of digitalisation and global integration intensify the need for a new governance paradigm – one that is adaptive, interdisciplinary, and grounded in the principles of sustainability and accountability.

The scientific novelty of this research lies in the development of a comprehensive model of legal analysis that integrates quantitative (bibliometric) and qualitative (content and SWOT) methods. It also reveals that the AI Act serves not only as a regulatory instrument but as a structural component of the European digital architecture, aligned with the goals of sustainable development.

The practical significance of the findings lies in their applicability for drafting Ukraine's national AI regulation strategy, preparing legislative proposals harmonised with EU law, and designing institutional mechanisms for managing digital transformation.

Future research perspectives include the development of a predictive legal framework capable of anticipating the effects of technological innovation; the exploration of quantum AI and its associated legal risks; the establishment of ethical standards for generative and autonomous systems; comparative analysis of national AI governance strategies across Asia, Europe, and North America; and examination of AI's impact on the evolution of sovereignty and public governance.

In conclusion, the formation of an effective system for AI governance requires not only the refinement of legal instruments but also the reconsideration of the philosophical and civilisational foundations of human–technology interaction.

Contemporary challenges – from the quantum acceleration of computation to the ethical risks of AI-enabled sabotage – demand the concerted efforts of law, science, and international institutions to shape a sustainable and secure future for the digital civilisation.

Author Contributions: Conceptualization, A.K.; methodology, A.K.; software, A.K.; validation, A.K. and O.N.R.; formal analysis, A.K. and O.N.R.; investigation, A.K. and O.N.R.; resources, A.K. and O.N.R.; data curation, A.K. and O.N.R.; writing-original draft preparation, A.K. and O.N.R.; writing-review and editing, A.K.; visualization, A.K.; supervision, A.K.; project administration, A.K.; funding acquisition, A.K. All authors have read and agreed to the published version of the manuscript.

Funding: The authors declare that no funding was received for the conduct of this research or the preparation of this article.

Data Availability Statement: All datasets and materials employed in the analytical and computational processes of this study are obtained from publicly accessible sources. Comprehensive references and hyperlinks to the original materials are provided within the manuscript to ensure full transparency and facilitate reproducibility. The data supporting the findings of this research are also available from the corresponding author upon reasonable request.

Acknowledgements: The authors would like to express their sincere gratitude to the reviewers, the academic editor, and the editorial team for their valuable comments and constructive recommendations, which have significantly contributed to improving the quality and clarity of this work.

Conflicts of Interest: The authors affirm no conflict of interest.

Appendix A

Analyze search results

[< Back to results](#)
Export Print Email

ALL(artificial AND intelligence) AND (LIMIT-TO(DOCTYPE, "ar") OR LIMIT-TO(DOCTYPE, "ch") OR LIMIT-TO(DOCTYPE, "cp") OR LIMIT-TO(DOCTYPE, "re") OR LIMIT-TO(DOCTYPE, "bk") OR LIMIT-TO(DOCTYPE, "ip") OR LIMIT-TO(DOCTYPE, "sh") OR LIMIT-TO(DOCTYPE, "dp") OR LIMIT-TO(DOCTYPE, "rp")) AND (LIMIT-TO(LANGUAGE, "English")) AND (LIMIT-TO(PUBYEAR, 1961) OR LIMIT-TO(PUBYEAR, 1962) OR LIMIT-TO(PUBYEAR, 1963) OR LIMIT-TO(PUBYEAR, 1964) OR LIMIT-TO(PUBYEAR, 1965) OR LIMIT-TO(PUBYEAR, 1966) OR LIMIT-TO(PUBYEAR, 1967) OR LIMIT-TO(PUBYEAR, 1968) OR LIMIT-TO(PUBYEAR, 1969) OR LIMIT-TO(PUBYEAR, 1970) OR LIMIT-TO(PUBYEAR, 1971) OR LIMIT-TO(PUBYEAR, 1972) OR LIMIT-TO(PUBYEAR, 1973) OR LIMIT-TO(PUBYEAR, 1974) OR LIMIT-TO(PUBYEAR, 1975) OR LIMIT-TO(PUBYEAR, 1976) OR LIMIT-TO(PUBYEAR, 1977) OR LIMIT-TO(PUBYEAR, 1978) OR LIMIT-TO(PUBYEAR, 1979) OR LIMIT-TO(PUBYEAR, 1980) OR LIMIT-TO(PUBYEAR, 1981) OR LIMIT-TO(PUBYEAR, 1982) OR LIMIT-TO(PUBYEAR, 1983) OR LIMIT-TO(PUBYEAR, 1984) OR LIMIT-TO(PUBYEAR, 1985) OR LIMIT-TO(PUBYEAR, 1986) OR LIMIT-TO(PUBYEAR, 1987) OR LIMIT-TO(PUBYEAR, 1988) OR LIMIT-TO(PUBYEAR, 1989) OR LIMIT-TO(PUBYEAR, 1990) OR LIMIT-TO(PUBYEAR, 1991) OR LIMIT-TO(PUBYEAR, 1992) OR LIMIT-TO(PUBYEAR, 1993) OR LIMIT-TO(PUBYEAR, 1994) OR LIMIT-TO(PUBYEAR, 1995) OR LIMIT-TO(PUBYEAR, 1996) OR LIMIT-TO(PUBYEAR, 1997) OR LIMIT-TO(PUBYEAR, 1998) OR LIMIT-TO(PUBYEAR, 1999) OR LIMIT-TO(PUBYEAR, 2000) OR LIMIT-TO(PUBYEAR, 2001) OR LIMIT-TO(PUBYEAR, 2002) OR LIMIT-TO(PUBYEAR, 2003) OR LIMIT-TO(PUBYEAR, 2004) OR LIMIT-TO(PUBYEAR, 2005) OR LIMIT-TO(PUBYEAR, 2006) OR LIMIT-TO(PUBYEAR, 2007) OR LIMIT-TO(PUBYEAR, 2008) OR LIMIT-TO(PUBYEAR, 2009) OR LIMIT-TO(PUBYEAR, 2010) OR LIMIT-TO(PUBYEAR, 2011) OR LIMIT-TO(PUBYEAR, 2012) OR LIMIT-TO(PUBYEAR, 2013) OR LIMIT-TO(PUBYEAR, 2014) OR LIMIT-TO(PUBYEAR, 2015) OR LIMIT-TO(PUBYEAR, 2016) OR LIMIT-TO(PUBYEAR, 2017) OR LIMIT-TO(PUBYEAR, 2018) OR LIMIT-TO(PUBYEAR, 2019) OR LIMIT-TO(PUBYEAR, 2020) OR LIMIT-TO(PUBYEAR, 2021) OR LIMIT-TO(PUBYEAR, 2022) OR LIMIT-TO(PUBYEAR, 2023) OR LIMIT-TO(PUBYEAR, 2024) OR LIMIT-TO(PUBYEAR, 2025) OR LIMIT-TO(PUBYEAR, 2026))

4,728,480 document results
Select year range to analyze: 1961 to 2026 View less ^ Analyze

Appendix B

Analyze search results

[< Back to results](#)
Export Print Email

TITLE-ABS-KEY("artificial intelligence" AND ("law" OR "legal framework" OR "legislation" OR "jurisprudence" OR "regulation" OR "regulatory" OR "governance" OR "policy" OR "compliance" OR "ethics" OR "human rights" OR "data protection" OR "privacy law"))

67,583 document results
Select year range to analyze: 1972 to 2026 Analyze

Appendix C

Analyze search results

[< Back to results](#)
Export Print Email

TITLE-ABS-KEY("artificial intelligence" AND ("law" OR "legal framework" OR "legislation" OR "jurisprudence" OR "regulation" OR "regulatory" OR "governance" OR "policy" OR "compliance" OR "ethics" OR "human rights" OR "data protection" OR "privacy law")) AND ("Ukraine" OR "Ukrainian" OR "European Union" OR "EU" OR "Europe" OR "Austria" OR "Belgium" OR "Bulgaria" OR "Croatia" OR "Cyprus" OR "Czech Republic" OR "Denmark" OR "Estonia" OR "Finland" OR "France" OR "Germany" OR "Greece" OR "Hungary" OR "Ireland" OR "Italy" OR "Latvia" OR "Lithuania" OR "Luxembourg" OR "Malta" OR "Netherlands" OR "Poland" OR "Portugal" OR "Romania" OR "Slovakia" OR "Slovenia" OR "Spain" OR "Sweden"))

5,240 document results
Select year range to analyze: 1986 to 2026 View less ^ Analyze

Appendix D

Analyze search results

[< Back to results](#)
Export Print Email

TITLE-ABS-KEY("Artificial Intelligence Act" OR "AI Act" OR "EU Directive on Artificial Intelligence") AND TITLE-ABS-KEY("Sustainable Development Goals" OR "SDGs" OR "Agenda 2030") AND TITLE-ABS-KEY(law OR legal OR regulation OR compliance OR governance)

5 document results
Select year range to analyze: 2022 to 2025 Analyze

Appendix E

Analyze search results

[Back to results](#)

[Export](#) [Print](#) [Email](#)

TITLE-ABS-KEY(("artificial intelligence" OR "AI") AND ("law" OR "legal framework" OR "legislation" OR "jurisprudence" OR "regulation" OR "regulatory" OR "governance" OR "policy" OR "compliance" OR "ethics" OR "human rights" OR "data protection" OR "privacy law") AND ("Ukraine" OR "Ukrainian"))

262 document results

Select year range to analyze: 2010 to 2026 [Analyze](#)

Appendix F

Analyze search results

[Back to results](#)

[Export](#) [Print](#) [Email](#)

TITLE-ABS-KEY(("artificial intelligence" OR "AI") AND ("law" OR "legal framework" OR "legislation" OR "jurisprudence" OR "regulation" OR "regulatory" OR "governance" OR "policy" OR "compliance" OR "ethics" OR "human rights" OR "data protection" OR "privacy law") AND ("Ukraine" OR "Ukrainian"))

11 document results

Select year range to analyze: 2023 to 2025 [Analyze](#)

Reference

1. Bećirović, S., & Mattoš, B. (2024). Artificial intelligence in the transformation of higher education: Threats, promises and implementation strategies. In M. D. Lytras, A. C. Serban, A. Alkhalidi, S. Malik, & T. Aldosemani (Eds.), *Digital transformation in higher education, Part A: Best practices and challenges*. Emerald Publishing Limited. <https://doi.org/10.1108/978-1-83549-480-620241002>.
2. Breiman, L. (2001). Random forests. *Machine Learning*, 45(1), 5–32. <https://doi.org/10.1023/A:1010933404324>.
3. Cath, C., Wachter, S., Mittelstadt, B., Taddeo, M., & Floridi, L. (2018). Artificial intelligence and the 'good society': The US, EU, and UK approach. *Science and Engineering Ethics*, 24(2), 505–528. <https://doi.org/10.1007/s11948-017-9901-7>.
4. Ciuladiene, G., & Walancik, K. (2022). Investigating Factors Hindering Intercultural Communication: Study of Ethnocentrism Level of Lithuanian and International Students. *Cultural Management: Science and Education*, 6(2), 47–56. <https://doi.org/10.30819/cmse.6-2.03>.
5. Ciuladiene, G., & Walancik, K., & Sevcuvianec, V. (2021). Ethnic-Based Cultural Differences: Study of Lithuania's Russian Minority. *Cultural Management: Science and Education*, 5 (2), 9–22. <https://doi.org/10.30819/cmse.5-2.01>.
6. Chkhikvishvili, G., & Beridze, S. (2024). Technological progress in international armed conflicts. *Works of Georgian Technical University*. <https://doi.org/10.36073/1512-0996-2024-2-294-300>.
7. Constantinides, M., Bogucka, E. P., Scepanovic, S., & Quercia, D. (2024). Good intentions, risky inventions: A method for assessing the risks and benefits of AI in mobile and wearable uses. *Proceedings of the ACM on Human-Computer Interaction*, 8(MHCI), Article 262. <https://doi.org/10.1145/3676507>.
8. Commercial Code of Ukraine, No. 436-IV. (2003, January 16). As amended up to January 1, 2020. Verkhovna Rada of Ukraine. <https://www.wipo.int/wipolex/en/legislation/details/19453>.
9. Constitution of Ukraine, adopted by the Verkhovna Rada of Ukraine on June 28, 1996. [https://www.coe.int/en/web/venice-commission/-/CDL\(1996\)058-e](https://www.coe.int/en/web/venice-commission/-/CDL(1996)058-e).
10. Dacko-Pikiewicz, Z. (2019). *The selected aspects of strategic management in the city divided by the border in the context of the development of the cross-border market of cultural services*. *Polish Journal of Management Studies*, 19(1), 130–144. <https://doi.org/10.17512/pjms.2019.19.1.10>.

11. Dzwigol, H., Kwilinski, A., Lyulyov, O., & Pimonenko, T. (2023). *Renewable energy, knowledge spillover and innovation: Capacity of environmental regulation*. *Energies*, 16(3), Article 1117. <https://doi.org/10.3390/en16031117>.
12. Dzwigol, H., Kwilinski, A., Lyulyov, O., & Pimonenko, T. (2024). Digitalization and Energy in Attaining Sustainable Development: Impact on Energy Consumption, Energy Structure, and Energy Intensity. *Energies*, 17(5), Article 1213. <https://doi.org/10.3390/en17051213>.
13. European Union. (2024). *Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024 laying down harmonised rules on artificial intelligence (Artificial Intelligence Act)*. Official Journal of the European Union, L 2024/1689, 12 July 2024. <http://data.europa.eu/eli/reg/2024/1689/oj>.
14. Gerke, S., Minssen, T., & Cohen, G. (2020). Ethical and legal challenges of artificial intelligence-driven healthcare. In A. Bohr & K. Memarzadeh (Eds.), *Artificial intelligence in healthcare* (pp. 295–336). Elsevier. <https://doi.org/10.1016/B978-0-12-818438-7.00012-5>.
15. Glaz'ev, S. Yu. (1993). *Teoriya dolgosrochnogo tekhniko-ekonomicheskogo razvitiya [The theory of long-term techno-economic development]*. Moskva: VlaDar.
16. Golyonko, O., Ulych, I., Ogir, O., & Dybach, O. (2025). Artificial intelligence in nuclear power: A review of promising areas and application specifics. *Nuclear and Radiation Safety*, 2(106), 66–79. [https://doi.org/10.32918/nrs.2025.2\(106\).07](https://doi.org/10.32918/nrs.2025.2(106).07).
17. Hamilton, R., & Strausz-Hupé, R. (1952). International technological progress. *The American Journal of Economics and Sociology*, 11(2), 119–132. <https://doi.org/10.1111/J.1536-7150.1952.TB00416.X>.
18. Hasanov, A., Tahirov, R., & Iskandarov, K. (2024). The future of warfare: Anticipated changes in military trends. *Social Development and Security*, 14(5), 1–18. <https://doi.org/10.33445/sds.2024.14.5.1>.
19. He, J., Baxter, S. L., Xu, J., Xu, J., Zhou, X., & Zhang, K. (2019). The practical implementation of artificial intelligence technologies in medicine. *Nature Medicine*, 25(1), 30–36. <https://doi.org/10.1038/s41591-018-0307-0>.
20. Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural Computation*, 9(8), 1735–1780. <https://doi.org/10.1162/neco.1997.9.8.1735>.
21. Hudima, T., & Kamyshanskyi, V. (2023). Artificial intelligence as a tool for digitalization of foreign economic policy: Peculiarities of legal regulation. *Financial and Credit Activity: Problems of Theory and Practice*, 3(50), 398–409. <https://doi.org/10.55643/fcaptop.3.50.2023.4039>.
22. Jiang, L., Xuan, Y., & Zhang, K. (2024). Unlocking innovation potential: The impact of artificial intelligence transformation on enterprise innovation capacity. *European Journal of Innovation Management*, 28(8), 4112–4131. <https://doi.org/10.1108/EJIM-07-2024-0809>.
23. Kabinet Ministriv Ukrainy. (2002, February 15). Postanova pro stvorennia yedynoi systemy zaluchennia, vykorystannia ta monitorynhu mizhnarodnoi tekhnichnoi dopomohy [Resolution on the creation of a unified system for attracting, using, and monitoring international technical assistance] No. 153. <https://zakon.rada.gov.ua/laws/show/153-2002-%D0%BF#Text>.
24. Kabinet Ministriv Ukrainy. (2019a, July 10). Rozporiadzhennia pro skhvalennia Stratehii rozvytku sfery innovatsiinoi diialnosti na period do 2030 roku [Resolution on the approval of the Strategy for the development of innovation activities until 2030] No. 526-r. <https://zakon.rada.gov.ua/laws/show/526-2019-%D1%80#Text>.
25. Kabinet Ministriv Ukrainy. (2019b, September 18). Postanova pytannia Ministerstva tsyfrovoi transformatsii [Resolution on issues of the Ministry of Digital Transformation] No. 856. <https://zakon.rada.gov.ua/laws/show/856-2019-%D0%BF#Text>.
26. Kabinet Ministriv Ukrainy. (2020, December 2). Rozporiadzhennia pro skhvalennia Kontseptsii rozvytku shtuchnoho intelektu v Ukraini [Resolution on the approval of the Concept for the Development of Artificial Intelligence in Ukraine] No. 1556-r. <https://zakon.rada.gov.ua/laws/show/1556-2020-%D1%80#Text>.

27. Khan, M. S., Umer, H., & Faruqe, F. (2024). Artificial intelligence for low income countries. *Humanities and Social Sciences Communications*, 11, Article 1422. <https://doi.org/10.1057/s41599-024-03947-w>.
28. Kaduk, D. Ye., Aleksandrova, T. M., Talapova, P. S., Agieieva, I. B., Ved, M. M., Trofymenko, M. O., Kolesnyk, M. R., & Nesmian, T. S. (2023). Current state and prospects of implementation of data standardization in the health care system of Ukraine (literature review). *Medicni Perspektivi*, 28(3), 190–198. <https://doi.org/10.26641/2307-0404.2023.3.289226>.
29. Kharazishvili, Y., & Kwilinski, A. (2022). *Methodology for determining the limit values of national security indicators using artificial intelligence methods*. *Virtual Economics*, 5(4), 7–26. [https://doi.org/10.34021/ve.2022.05.04\(1\)](https://doi.org/10.34021/ve.2022.05.04(1)).
30. Kharazishvili, Y., Kwilinski, K., Ivaniuta, S., Sukhodolia, O., & Czart, P. (2025). *System of indicators for the environmental component of sustainable development in the security dimension*. *Sustainable Development*, 33(S1), 146–160. <https://doi.org/10.1002/sd.70000>.
31. Kondratiev, N. D. (1925). Bol'shie tsikly kon'iunktury [The major economic cycles]. *Voprosy kon'iunktury* [Problems of Conjunction], 1(1), 28–79.
32. Kozlovskiy, S., Kulinich, T., Lavrov, R., Zayukov, I., Kozlovskiy, A., & Kozlovskiy, O. (2025). Modelling and forecasting the exchange rate in Ukraine using artificial intelligence methods. *Financial and Credit Activity: Problems of Theory and Practice*, 3(62), 144–162. <https://doi.org/10.55643/fcaptop.3.62.2025.4716>.
33. Krasnoselskiy, M. V., Artamonova, N. O., Sukhina, O. M., Rublova, T. V., & Pavlichenko, Y. V. (2025). Plagiarism in the system of academic integrity in medical research (part 2). *Ukrainian Journal of Radiology and Oncology*, 33(1), 113–128. <https://doi.org/10.46879/ukroj.1.2025.113-128>.
34. Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). ImageNet classification with deep convolutional neural networks. In *Advances in Neural Information Processing Systems* (Vol. 2, pp. 1097–1105). Curran Associates, Inc. <https://doi.org/10.1145/3065386>.
35. Kuziemski, M., & Misuraca, G. (2020). AI governance in the public sector: Three tales from the frontiers of automated decision-making in democratic settings. *Telecommunications Policy*, 44(6), Article 101976. <https://doi.org/10.1016/j.telpol.2020.101976>.
36. Kwilinski, A. (2023). The relationship between sustainable development and digital transformation: Bibliometric analysis. *Virtual Economics*, 6(3), 56–69. [https://doi.org/10.34021/ve.2023.06.03\(4\)](https://doi.org/10.34021/ve.2023.06.03(4)).
37. Kwilinski, A. (2024). *Understanding the nonlinear effect of digital technology development on CO₂ reduction*. *Sustainable Development*, 32(5), 5797–5811. <https://doi.org/10.1002/sd.2964>.
38. Kwilinski, A. (2025). *GDP per capita vs foreign direct investment: Key drivers of a country's technological leadership*. *Technological and Economic Development of Economy*, 31(5), 1320–1344. <https://doi.org/10.3846/tede.2025.22857>.
39. Kwilinski, A., Lyulyov, O., & Pimonenko, T. (2023a). *The coupling and coordination degree of digital business and digital governance in the context of sustainable development*. *Information*, 14(12), Article 651. <https://doi.org/10.3390/info14120651>.
40. Kwilinski, A., Lyulyov, O., & Pimonenko, T. (2023b). *The impact of digital business on energy efficiency in EU countries*. *Information*, 14(9), Article 480. <https://doi.org/10.3390/info14090480>.
41. Kwilinski, A., Lyulyov, O., & Pimonenko, T. (2024a). *Sustainable development in the European Union: Managing artificial intelligence technology for green economic growth*. *Polish Journal of Management Studies*, 30(1), 187–207. <https://doi.org/10.17512/pjms.2024.30.1.11>.
42. Kwilinski, A., Lyulyov, O., & Pimonenko, T. (2024b). *Green economic development and entrepreneurship transformation*. *Entrepreneurial Business and Economics Review*, 12(4), 157–175. <https://doi.org/10.15678/EBER.2024.120409>.

43. Kwiliński, A., Merritt, P., & Wróblewski, Ł. (2024c). *Advancing sustainable development goals through digital culture: A global research overview*. *Cultural Management: Science and Education*, 8(1), 61–80. <https://doi.org/10.30819/cmse.8-1.04>.
44. Kwilinski, A., Lyulyov, O., & Pimonenko, T. (2025a). *The culture of sustainable governance for green economic development*. *Cultural Management: Science and Education*, 9(1), 71–94. <https://doi.org/10.30819/cmse.9-1.04>.
45. Kwilinski, A., Lyulyov, O., & Pimonenko, T. (2025b). *Population literacy and ICT skills: Drivers of net migration growth*. *Central European Business Review*, 14(3), 45–63. <https://doi.org/10.18267/j.cebr.388>.
46. Kwiliński, A., Dacko-Pikiewicz, Z., Szczepańska-Woszczyna, K., Lyulyov, O., & Pimonenko, T. (2025c). *The role of innovation in the transition to a green economy: A path to sustainable growth*. *Journal of Open Innovation: Technology, Market, and Complexity*, 11(2), Article 100530. <https://doi.org/10.1016/j.joitmc.2025.100530>.
47. Kwilinski, A., Lyulyov, O., & Pimonenko, T. (2025d). *The role of innovation development in advancing green finance*. *Journal of Risk and Financial Management*, 18(3), Article 140. <https://doi.org/10.3390/jrfm18030140>.
48. Kwilinski, A., Lyulyov, O., & Pimonenko, T. (2025e). *The role of green finance in attaining environmental sustainability within a country's ESG performance*. *Journal of Innovation & Knowledge*, 10(2), 1 Article 00674. <https://doi.org/10.1016/j.jik.2025.100674>.
49. LeCun, Y., Bengio, Y., & Hinton, G. (2015). *Deep learning*. *Nature*, 521(7553), 436–444. <https://doi.org/10.1038/nature14539>.
50. Lyulyov, O., Pimonenko, T., Infante-Moro, A., & Kwilinski, A. (2024). *Perception of artificial intelligence: GSR analysis and face detection*. *Virtual Economics*, 7(2), 7–30. [https://doi.org/10.34021/ve.2024.07.02\(1\)](https://doi.org/10.34021/ve.2024.07.02(1)).
51. McCarthy, J., Minsky, M. L., Rochester, N., & Shannon, C. E. (1955). *A proposal for the Dartmouth Summer Research Project on Artificial Intelligence*. Hanover, NH: Dartmouth College. <http://jmc.stanford.edu/articles/dartmouth/dartmouth.pdf>.
52. Muehlematter, U. J., Daniore, P., & Vokinger, K. N. (2021). *Approval of artificial intelligence and machine learning-based medical devices in the USA and Europe (2015–20): A comparative analysis*. *The Lancet Digital Health*, 3(3), e195–e203. [https://doi.org/10.1016/S2589-7500\(20\)30292-2](https://doi.org/10.1016/S2589-7500(20)30292-2).
53. Mumford, L. (1970). *The Myth of the Machine (Vol. II): The Pentagon of Power*. New York: Harcourt Brace Jovanovich.
54. Nikitenko, V. (2024). *Philosophy of war: Impact on social development and scientific & technological progress*. *Bulletin of the National Technical University “KhPI”. Series: Actual Problems of Ukrainian Society Development*, 2, 24–30. <https://doi.org/10.20998/2227-6890.2023.2.05>.
55. Odrekivskyy, M., Darimits, R., & Zhezhukha, V. (2022). *Intellectual information systems for monitoring the competences of managers of innovative enterprises*. *Financial and Credit Activity: Problems of Theory and Practice*, 5(46), 222–238. <https://doi.org/10.55643/fcaptive.5.46.2022.3884>.
56. Osyodlo, G. V., Kominko, L. V., & Vovkodav, A. M. (2025). *Development of the ethical code concept for using of artificial intelligence in military medical education: The Ukrainian Military Medical Academy's approach*. *Ukrains'kij Zurnal Vijskovoï Medicini*, 6(2), 14–23. [https://doi.org/10.46847/ujmm.2025.2\(6\)-014](https://doi.org/10.46847/ujmm.2025.2(6)-014).
57. Panda, M., Hossain, M. M., Puri, R., & Ahmad, A. (2025). *Artificial intelligence in action: Shaping the future of public sector*. *Digital Policy, Regulation and Governance*, 27(6), 668–686. <https://doi.org/10.1108/DPRG-10-2024-0272>.
58. Prazian, M. (2025). *An interdisciplinary approach to powering artificial intelligence (AI)*. *Nuclear and Radiation Safety*, 1(105), 27–34. [https://doi.org/10.32918/NRS.2025.1\(105\).03](https://doi.org/10.32918/NRS.2025.1(105).03).

59. Price, D. J. de Solla. (1951). Quantitative measures of the development of science. *Archives internationales d'histoire des sciences*, 14(54), 85–93.
60. PRISMA Guidelines. (2020). <http://www.prisma-statement.org/?AspxAutoDetectCookieSupport=1>.
61. Putiienko, O. O., Panchenko, I. O., Mogilevskyy, S. Y., Zhupan, B. B., Denysiuk, O. Y., & Gulida, A. O. (2025). Specifics of teaching the topic “Ocular changes in diabetes mellitus: classification, etiology, pathogenesis, risk factors. Algorithm for early diagnosis” under wartime conditions. *Archive of Ukrainian Ophthalmology*, 13(1), 63–67. <https://doi.org/10.22141/2309-8147.13.1.2025.405>.
62. Ronneberger, O., Fischer, P., & Brox, T. (2015). U-net: Convolutional networks for biomedical image segmentation. In N. Navab, J. Hornegger, W. M. Wells, & A. F. Frangi (Eds.), *Lecture Notes in Computer Science* (Vol. 9351, pp. 234–241). Springer. https://doi.org/10.1007/978-3-319-24574-4_28.
63. Ryan, M., & Stahl, B. C. (2021). Artificial intelligence ethics guidelines for developers and users: Clarifying their content and normative implications. *Journal of Information, Communication and Ethics in Society*, 19(1), 61–86. <https://doi.org/10.1108/JICES-12-2019-0138>.
64. Senato della Repubblica. (2025). *Disposizioni e deleghe al Governo in materia di intelligenza artificiale (Atto Senato n. 1146, XIX Legislatura)*. [Provisions and Delegations to the Government on Artificial Intelligence (Senate Act No. 1146, 19th Legislature)]. Approved by the Senate on March 20, 2025. <https://www.senato.it/leggi-e-documenti/disegni-di-legge/scheda-ddl?did=58262>.
65. Scopus data. (2025). <https://www.scopus.com/>.
66. Skydan, O., Brodsky, Y., Topolnytsky, P., & Pivovar, P. (2019). Space technologies in the production system of agricultural producers. *Scientific Horizons*, 4, 3–12. <https://doi.org/10.33249/2663-2144-2019-77-4-3-12>.
67. State Service for Special Communications and Information Protection of Ukraine. (2025). Latest technologies and cybersecurity are in the spotlight: specialists of the State Special Communications Service took part in the NATO conference “TIDE Sprint 2025”. *The official portal of the State Service for Special Communications and Information Protection of Ukraine*. <https://cip.gov.ua/ua/news/novitni-tekhnologiyi-ta-kiberbezpeka-u-centri-uvagi-fakhivci-derzhspeczv-yazku-vzyali-uchast-u-konferencyi-nato-tide-sprint-2025>.
68. Stepanov, Yu. M., & Zyhalo, E. V. (2020). Indices of heart rate variability for estimation of adaptive processes and stress resistance in gastroenterology practice (using up-to-date technology of precise-diagnosis). *Gastroenterology*, 54(2), 113–123. <https://doi.org/10.22141/2308-2097.54.2.2020.206230>.
69. Thirakulwanich, A., Szczepańska-Woszczyna, K., & Kot, S. (2025). Policy instruments and green indicators in the diffusion of green innovation: A comparative analysis of Poland and Thailand. *Challenges in Sustainability*, 13(1), 35–47. <https://doi.org/10.56578/cis130103>.
70. Tjoa, S., Temper, P. K. M., Zanol, J., Wagner, M., & Holzinger, A. (2022). AIRMan: An Artificial Intelligence (AI) risk management system. In *Proceedings of the 2022 2nd International Conference on Advanced Enterprise Information System (AEIS 2022)* (pp. 72–81). IEEE. <https://doi.org/10.1109/AEIS59450.2022.00017>.
71. Tjokro, G., Zaenuri, Z., Yanto, H., Rokhman, F., Rajagukguk, A., & Sanni, T. (2025). Reforming legal frameworks for human capital: Digital strategies driving Industry 5.0 and sustainability. *Journal of Law and Legal Reform*, 6(3), 45–94. <https://doi.org/10.15294/jllr.v6i3.22645>.
72. Tsyvilnyi kodeks Ukrainy [Civil Code of Ukraine], January 16, 2003, No. 435-IV (Vidomosti Verkhovnoi Rady Ukrainy, 2003, Nos. 40–44, Art. 356). <https://zakon.rada.gov.ua/laws/show/435-15#Text>.

73. Tun, H. M., Naing, L., Malik, O. A., & Rahman, H. A. (2025). Navigating ASEAN region Artificial Intelligence (AI) governance readiness in healthcare. *Health Policy and Technology*, 14(2), Article 100981. <https://doi.org/10.1016/j.hlpt.2025.100981>.
74. Turing, A. M. (1950). Computing machinery and intelligence. *Mind*, 59(236), 433–460. <https://doi.org/10.1093/mind/LIX.236.433>.
75. Uhoda pro asotsiatsiiu mizh Ukrainoiu, z odniiei storony, ta Yevropeiskym Soiuzom, Yevropeiskym spivtovarystvom z atomnoi enerhii i yikhnimy derzhavamy-chlenamy, z inshoi storony [Association Agreement between the European Union and the European Atomic Energy Community and their Member States, of the one part, and Ukraine, of the other part], March 21, 2014 & June 27, 2014, Brussels. Ratified by Law No. 1678-VII, September 16, 2014. https://zakon.rada.gov.ua/laws/show/984_011#Text.
76. United Nations. (2015). The 17 Goals. <https://sdgs.un.org/goals>.
77. van Norren, D. E. (2023). The ethics of artificial intelligence, UNESCO and the African Ubuntu perspective. *Journal of Information, Communication and Ethics in Society*, 21(1), 112–128. <https://doi.org/10.1108/JICES-04-2022-0037>.
78. VOSviewer. (2025). <https://www.vosviewer.com/features/examples>
79. Walancik, K. (Ed.). (2024). *Edukacja wielokulturowa: Strategie edukacyjne*. Wydawnictwo Naukowe Akademii WSB.
80. Wiener, N. (1948). *Cybernetics or Control and Communication in the Animal and the Machine*. The MIT Press.
81. Yang, Q., Liu, Y., Cheng, Y., Kang, Y., Chen, T., & Yu, H. (2020). *Federated learning*. Morgan and Claypool Publishers. <https://doi.org/10.2200/S00960ED2V01Y201910AIM043>.
82. Yap, S. N. (2025). AI governance for sustainable development: Lessons for Malaysia from the EU AI Act. In *Integrating legal compliance with sustainable development goals* (pp. 327–354). IGI Global. <https://doi.org/10.4018/979-8-3373-1792-2.ch011>.
83. Zakon Ukrainy “Pro avtorske pravo i sumizhni prava” [Law of Ukraine “On Copyright and Related Rights”] No. 2811-IX, December 1, 2022 (Vidomosti Verkhovnoi Rady Ukrainy, 2023, No. 57, Art. 166). <https://zakon.rada.gov.ua/laws/show/2811-20#Text>.
84. Zakon Ukrainy “Pro Derzhavnu sluzhbu spetsialnoho zviazku ta zakhystu informatsii Ukrainy” [Law of Ukraine “On the State Service of Special Communications and Information Protection of Ukraine”] No. 3475-IV, February 23, 2006 (Vidomosti Verkhovnoi Rady Ukrainy, 2006, No. 30, Art. 258). <https://zakon.rada.gov.ua/laws/show/3475-15#Text>.
85. Zakon Ukrainy “Pro hromadski obiednannia” [Law of Ukraine “On Public Associations”] No. 4572-VI, March 22, 2012 (Vidomosti Verkhovnoi Rady Ukrainy, 2013, No. 1, Art. 1). <https://zakon.rada.gov.ua/laws/show/4572-17#Text>.
86. Zakon Ukrainy “Pro innovatsiinu diialnist” [Law of Ukraine “On Innovation Activity”] No. 40-IV, July 4, 2002 (Vidomosti Verkhovnoi Rady Ukrainy, 2002, No. 36, Art. 266). <https://zakon.rada.gov.ua/laws/show/40-15#Text>.
87. Zakon Ukrainy “Pro investytsiinu diialnist” [Law of Ukraine “On Investment Activity”] No. 1560-XII, September 18, 1991 (Vidomosti Verkhovnoi Rady Ukrainy, 1991, No. 47, Art. 646). <https://zakon.rada.gov.ua/laws/show/1560-12#Text>.
88. Zakon Ukrainy “Pro mizhnarodni dohovory Ukrainy” [Law of Ukraine “On International Treaties of Ukraine”] No. 1906-IV, June 29, 2004 (Vidomosti Verkhovnoi Rady Ukrainy, 2004, No. 50, Art. 540). <https://zakon.rada.gov.ua/laws/show/1906-15#Text>.
89. Zakon Ukrainy “Pro natsionalnu bezpeku Ukrainy” [Law of Ukraine “On National Security of Ukraine”] No. 2469-VIII, June 21, 2018 (Vidomosti Verkhovnoi Rady Ukrainy, 2018, No. 31, Art. 241). <https://zakon.rada.gov.ua/laws/show/2469-19#Text>.
90. Zakon Ukrainy “Pro naukovu i naukovo-tekhnicnu diialnist” [Law of Ukraine “On Scientific and Scientific-Technical Activity”] No. 848-VIII, November 26, 2015 (Vidomosti Verkhovnoi Rady Ukrainy, 2016, No. 3, Art. 25). <https://zakon.rada.gov.ua/laws/show/848-19#Text>.

91. Zakon Ukrainy “Pro osvitu” [Law of Ukraine "On Education"] No. 2145-VIII, September 5, 2017 (Vidomosti Verkhovnoi Rady Ukrainy, 2017, Nos. 38–39, Art. 380).
<https://zakon.rada.gov.ua/laws/show/2145-19#Text>.
92. Zakon Ukrainy “Pro pravovyi status inozemtsiv ta osib bez hromadianstva” [Law of Ukraine "On the Legal Status of Foreigners and Stateless Persons"] No. 3773-VI, September 22, 2011 (Vidomosti Verkhovnoi Rady Ukrainy, 2012, Nos. 19–20, Art. 179).
<https://zakon.rada.gov.ua/laws/show/3773-17#Text>.
93. Zakon Ukrainy “Pro vyshchu osvitu” [Law of Ukraine "On Higher Education"] No. 1556-VII, July 1, 2014 (Vidomosti Verkhovnoi Rady Ukrainy, 2014, Nos. 37–38, Art. 2004).
<https://zakon.rada.gov.ua/laws/show/1556-18#Text>.
94. Zhylka, N. Y., Shcherbinska, O. S., & Netskar, I. P. (2022). The prospects for the use of artificial intelligence in obstetrics in Ukraine: Literature review. *Reproductive Endocrinology*, 66, 39–45.
<https://doi.org/10.18370/2309-4117.2022.66.39-45>.

Revisiting Self-Determination Theory in the Prestige Economy of Science: Implications for Academic Motivation

Lukasz Sulkowski ^{1*}, Justyna Dziedzic ², Sylwia Przytula ³, Robert Seliga ⁴

¹ WSB University, Dabrowa Gornicza, Poland
ORCID: 0000-0002-1248-2743
e-mail: lsulkowski@wsb.edu.pl

² University of Social Sciences, Lodz, Poland
ORCID: 0000-0002-8292-0892
e-mail: jdziedzic@san.edu.pl

³ Wroclaw University of Science and Technology, Wroclaw, Poland
ORCID: 0000-0002-9602-241X
e-mail: sylwia.przytula@pwr.edu.pl

⁴ WSB University, Dabrowa Gornicza, Poland
ORCID: 0000-0003-3306-904X
e-mail: robert.seliga@wsb.edu.pl

* Corresponding author: Lukasz Sulkowski, lsulkowski@wsb.edu.pl

Abstract

Academic motivation has traditionally been analysed through the lens of Self-Determination Theory (SDT), which emphasises autonomy, competence, and relatedness as essential psychological needs. However, in contemporary higher education, the economy of prestige plays an increasingly influential role in shaping academic behaviour, recognition, and career progression. This study addresses the gap in understanding how prestige influences the interplay between intrinsic and extrinsic motivations in academic contexts. The main aim of the study is to expand the theoretical framework of SDT by integrating the concept of prestige as a critical factor influencing academic motivation. The study develops a conceptual model that integrates prestige into SDT and empirically examines its operation through qualitative interviews with Polish academics, thus addressing a gap in motivation theory and contextualising it within the prestige economy of higher education. This qualitative study employed an interpretative-symbolic paradigm and conducted in-depth interviews with 11 academics from diverse disciplines and institutions in Poland. The data were analysed using thematic coding and triangulated by multiple researchers to ensure validity. The participants were selected purposively to capture a range of experiences related to academic motivation, prestige, and institutional dynamics. The findings reveal that prestige functions simultaneously as an intrinsic and extrinsic motivator. It enhances recognition, provides access to resources, and strengthens perceived competence and relatedness. However, it can also limit autonomy and creativity when academics align their work with dominant prestige norms. The study also finds that prestige shapes collaboration patterns, affects gendered access to academic recognition, and influences identity formation among scholars. By incorporating prestige into the SDT model, this paper offers a novel conceptual expansion of motivation theory in academia. It highlights how symbolic capital intersects with psychological needs and reveals the socio-cultural forces shaping motivation in higher education. This framework has implications for research on academic identity, resilience, and organisational behaviour. The study suggests that academic institutions should develop policies that support autonomy and

Cite as:

Sulkowski, L., Dziedzic, J., Przytula, S., & Seliga, R. (2025). Revisiting Self-Determination Theory in the Prestige Economy of Science: Implications for Academic Motivation. *Forum Scientiae Oeconomia*, 13(3), 53–67.
https://doi.org/10.23762/FSO_V OL13_NO3_2

Received: 10 January 2025

Revised: 15 July 2025

Accepted: 10 September 2025



Copyright: © 2025 by the authors. For open-access publication within the terms and conditions of the Creative Commons Attribution (CC BY) licence (<https://creativecommons.org/licenses/by/4.0/>).

intrinsic motivation while acknowledging the role of prestige. Strategies to balance recognition structures with individual well-being and ethical conduct are essential to fostering sustainable academic environments. The findings also inform leadership and policy-making in higher education regarding career evaluation systems and research funding mechanisms.

Key words

self-determination theory, academic motivation, prestige economy, intrinsic and extrinsic motivation, higher education.

Introduction

SDT provides a thorough perspective on human motivation, highlighting the importance of inner and extrinsic incentives in influencing action. The research, described in Deci and Ryan's seminal 1985 paper, has gained widespread acceptance across diverse domains such as education, business, healthcare, and sports. SDT uncovers the factors that motivate individuals and guides them in creating situations that support their natural inclination towards personal development. According to Deci and Ryan's 2000 results, SDT distinguishes between intrinsic motivation, which arises from the enjoyment of the activity itself, and extrinsic motivation, which derives from the practical utility of the activity. Although intrinsic motivation is typically considered more persistent and desirable, SDT acknowledges that behaviours driven by extrinsic motivation can transform into self-determined actions through internalisation and integration.

The "economy of prestige" concept is a strong and well-established paradigm that is particularly relevant in several professional fields, particularly academics (Blackmore, 2015). The text elucidates the pursuit of recognition and esteem as rewards within particular domains. Bourdieu (1986) studied the symbolic capital subject in 80', while F. English conducted a similar study on it in 2005. In the academic sphere, prestige has a considerable impact. It influences decisions on research topics, the selection of publications, partnerships, and even teaching-related tasks. Academics compete for a few prestigious chances, such as tenured positions, financial resources, accolades, publications, and invitations to present at conferences or contribute to influential journals (Merton, 1973; Lamont, 2012; Kwiek, 2021). Prestige serves as both an inherent and external motivator in academic settings. The desire for prestige can be interpreted as a quest for individual gratification and intellectual recognition. Externally, it yields tangible benefits such as job advancement, increased opportunities for financial gain, and a more substantial presence in the academic domain (Zuckerman, 1977; Long, 2001). Specifically, this study develops and tests a conceptual model that incorporates prestige into SDT, while also providing a contextual application in Poland. In doing so, it identifies a theoretical gap in understanding how prestige interacts with autonomy, competence, and relatedness, offering both conceptual innovation and empirical validation.

This work employs a qualitative research methodology, conducting in-depth interviews to investigate the expanded model of SDT. The interviews were conducted with academics of diverse international origins from various disciplines affiliated with higher education institutions. The sample used for the interviews was carefully selected to include a wide range of participants.

1. Literature review

One of SDT's unique contributions to psychological, sociological, and management research is the integration of autonomy, competence, and relatedness demands into a cohesive theory of human motivation. Autonomy refers to the need for individuals to experience a sense of control over their actions and act with deliberate choice. According to SDT, people who make choices willingly have higher levels of motivation and engagement. On the other hand, when individuals feel compelled or pressured, their motivation and engagement decrease in quality (Deci & Ryan, 2000). Competence is feeling capable and confident in one's environment, achieved by successfully mastering and

overcoming appropriately challenging activities. The innate desire to effectively engage with one's surroundings and attain success is heightened by offering suitable challenges, positive feedback, and sufficient support (Vallerand, 1997).

Deci and Ryan propose that when extrinsic motivators are fully integrated into an individual's values and sense of self, they might transform into 'autonomous extrinsic motivations' that closely resemble intrinsic motivation regarding their quality and outcomes (Deci & Ryan, 1985; 2000). Niemiec and Ryan (2009) discovered that teaching approaches that promote autonomy positively correlate with student involvement and satisfaction, which improves academic achievement. A meta-analysis by Taylor et al. (2014) consolidated findings from multiple studies and concluded that autonomy-supportive teaching practices significantly enhance students' intrinsic motivation across various educational levels and disciplines.

Meeting the psychological needs outlined in SDT is associated with increased job satisfaction and decreased burnout among faculty members. Deci et al. (1991) found that university professors with high autonomy and competence exhibited higher motivation and job satisfaction. Additionally, studies (Jeno et al., 2018; Olsen & Mason, 2023) have shown that higher perceived autonomy among faculty members correlates with greater job satisfaction and a higher intent to remain in their positions.

SDT has also been used to understand the motivations behind academic research productivity. A study by Sheldon and Krieger (2007) applied SDT to explore how law school environments impacted the well-being and motivations of law professors, finding that those in supportive environments that nurtured autonomy and competence were happier and more productive. This aligns with research by Amabile et al. (1994), which found that scientists who felt their work supported their intrinsic needs were more likely to produce widely recognised research.

The universality of SDT's principles has been explored in different cultural contexts within academia. Chirkov et al. (2003) examined the applicability of SDT in non-Western settings and found that the basic psychological needs identified by SDT are indeed universal. However, the ways these needs are satisfied can vary significantly across cultures. This highlights the adaptability of SDT in understanding academic motivation globally.

Academic researchers often select projects more likely to result in publications in prestigious journals or attract attention from influential peers (Sulkowski, 2023; Przytula et al., 2023). Kieser and Leiner (2009) have examined the persistent gap between rigor and relevance in management research, arguing that this gap is inherently unbridgeable due to fundamental differences in the objectives and methodologies of academic research and practical management. Publications in high-ranking journals enhance a researcher's reputation and significantly affect their career prospects, such as tenure and promotion. Brembs et al. (2013) discuss how this pressure leads to strategic behaviours such as salami slicing (publishing minimal publishable units) and a preference for quantity over quality to maximize output and perceived prestige (Brembs et al., 2013). Furthermore, the role of personal branding in the reflexive construction of organizational identity highlights how scientists navigate their professional image within academic institutions (Dziedzic & Sulkowski, 2023).

While SDT explains motives arising from autonomy, competence, and relatedness, incorporating prestige provides a more comprehensive perspective. Prestige, typically attained through scholarly achievements and professional acknowledgements, is a substantial external incentive impacting professional paths, research prospects, and teaching responsibilities (Merton, 1973). The pursuit of prestige is motivated by the aspiration for personal acclaim and the advantages that such a position might bestow within the academic community.

Prestige has been analysed by economists and sociologists using the concept of "symbolic capital," a phrase coined by Bourdieu (1986) to refer to the resources individuals or groups possess regarding prestige, honour, and attention within a specific social context. Symbolic capital in academia is crucial in determining one's access to resources, shaping career chances, and influencing scholarly output and innovation (Lamont, 2009). English (2005) describes the concept of the economy of prestige,

which highlights how a competitive marketplace for prestigious posts and recognitions with limited availability shapes academic areas. This rivalry may incentivise researchers to align their research ideas or methodology with those more likely to achieve prestige rather than focusing on personal interests or addressing broader social needs (Hermanowicz, 1998).

Cummings and Kiesler (2008) argue that cross-disciplinary collaboration can enhance innovation by integrating diverse perspectives, although challenges such as communication barriers and differing norms exist. Prestige plays a significant role in collaboration, as working with esteemed colleagues can increase the perceived value of research, visibility, and career opportunities (Walsh & Maloney, 2007).

Research shows that gender disparities exist in acquiring prestige, with women often facing more significant obstacles than men. Van den Brink and Benschop (2012) attribute these disparities to gender biases in academic evaluations, which influence career trajectories for female academics. Integrating SDT (SDT) with the economy of prestige illustrates how pursuing prestige can limit the freedom to choose research topics based on personal interests, shifting focus toward topics that yield higher status rewards (Vallerand, 1997). Relationships within academia often form based on intellectual compatibility and strategic prestige, with collaborations to enhance reputation (Willmott, 2011).

The expectation of attaining and sustaining a high status might result in stress, exhaustion, and possibly immoral actions such as manipulating data or engaging in excessive competition (Anderson et al., 2007). Future discussions and legislation regarding academic motives should consider these processes to foster a healthy balance between the quest for prestige and the development of intrinsic motivation.

Furthermore, integrating prestige into SDT helps to contextualize academic motivations within a broader socio-cultural framework. It acknowledges that academics do not operate in a vacuum but are influenced by their communities' broader values and recognition structures (Lamont, 2009). Prestige can enhance autonomy by allowing academics greater freedom to pursue their interests (Vallerand, 1997). However, the desire for recognition can also limit autonomy, making academics conform to mainstream topics and methodologies more likely to be rewarded, potentially stifling creativity and genuine scholarly inquiry (English, 2005).

Prestige directly influences perceptions of competence. Achievements that garner prestige, such as publishing in top journals or receiving prestigious awards, serve as public affirmations of an academic's competence. This external validation can enhance an individual's self-efficacy and motivation, encouraging further effort and engagement in their field (Deci & Ryan, 1985). However, this dynamic can also lead to a competence-pursuit imbalance where the external indicators of success (e.g., citation counts, impact factors) become the primary drivers of activity, overshadowing deeper, more intrinsic engagements with research topics (Merton, 1973).

Prestige impacts relatedness in that high-status individuals or groups often attract more collaboration opportunities, which can enhance feelings of connectedness and belonging within the academic community (Ryan & Deci, 2001). Nevertheless, an overemphasis on prestige can disrupt genuine collegial relationships, fostering competition over collaboration. This environment can undermine the supportive peer interactions essential for satisfying the need for relatedness, leading to isolation and alienation (Bourdieu, 1986). Given these interactions, prestige can be conceptualised as a fundamental principle in the academic world alongside autonomy, competence, and relatedness within the SDT framework (Figure 1).

The expanded model (Figure 1) acknowledges that while the traditional SDT needs, autonomy, competence, and relatedness, significantly influence motivation, the addition of prestige reflects a key external factor interacting with these needs. Prestige incorporates socio-cultural and institutional influences, offering a more holistic view of academic motivations (Lamont, 2009). Although intrinsic needs enhance well-being and motivation, the academic economy also relies on prestige, creating a balancing act between intrinsic and extrinsic rewards. Academic institutions need to support

autonomy, competence, and relatedness while aligning these needs with prestige dynamics (Willmott, 2011).

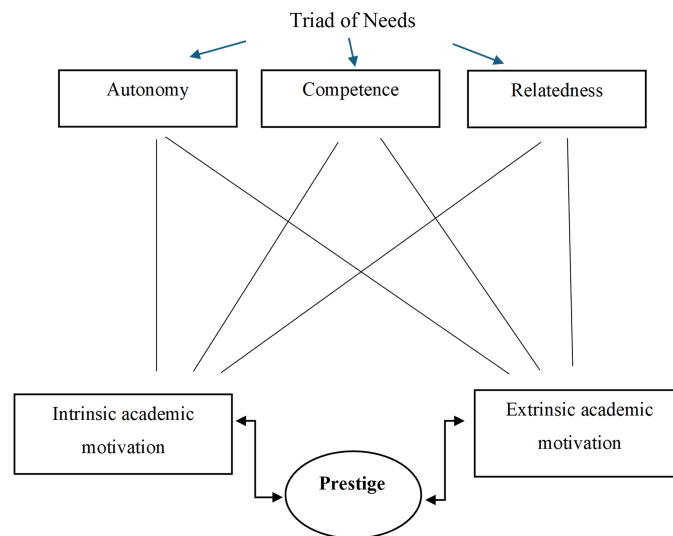


Figure 1. Prestige-Enhanced SDT Model for Academic Motivation.

Source: own study.

The following examples illustrate how the core principles of SDT, autonomy, competence, and relatedness, manifest in diverse academic settings and influence motivation, resilience, and the formation of identity. Building academic resilience through mentoring, collegial networks, and supportive institutional cultures fosters intrinsic motivation and adaptive capacity, particularly among early-career researchers facing a volatile higher education environment (Ross et al., 2023). The disrupted trajectories of female scholars, shaped by intersecting roles such as caregiving and minority status, further highlight the need for institutional policies that promote autonomy, equity, and intrinsic motivation across academic careers (Shorey et al., 2023). Similarly, the experience of professional vulnerability among Chinese academics, driven by performative pressures and institutional constraints, emphasises the importance of autonomy-supportive environments that enable reflective agency and preserve internal motivation (Gao & Yuan, 2024). Although toxic leadership can undermine mental health, academic staff may maintain their work engagement, illustrating the complex relationship between external control and intrinsic motivation (Klahn Acuña & Male, 2024). Research also shows that parenting style can enhance academic resilience by boosting self-efficacy and motivation, supporting the development of self-determined learners (Shengyao et al., 2024). Finally, academics transitioning into professional master's programmes often face identity tensions, yet their proactive engagement in workplace learning reflects efforts to sustain autonomy, competence, and relatedness in unfamiliar academic contexts (Li & Tao, 2025).

The research questions aimed to understand how intrinsic and extrinsic motivations influence academic work. Building on these unresolved debates, this study is guided by the following research questions: RQ1: How does pursuing prestige influence academics' motivations within the SDT framework? RQ2: How does academic prestige impact collaborative networks and institutional connections among academics? RQ3: How does the pursuit of prestige influence the autonomy of academics in their professional work and decision-making?

2. Methodology

This study adopted an interpretative-symbolic paradigm and a descriptive-explanatory methodology to explore the complex interplay between the traditional SDT needs, autonomy, competence, and relatedness, and the additional prestige factor within academic settings. The study utilised a qualitative research approach to explore academics' motivational and emotional belief

patterns within the context of SDT and the prestige economy of science. The interview guide was designed based on the SDT framework (autonomy, competence, relatedness) and prior research on academic prestige (Blackmore, 2015; Bourdieu, 1986; Merton, 1973). Questions were semi-structured to allow comparability across interviews while leaving space for individual elaboration. The guide was reviewed by colleagues for content validity, and a pilot interview with one academic was conducted to refine clarity, sequencing, and wording.

The study involved eleven academics from both public and private higher education institutions in Poland. Participants were purposively selected to ensure diversity in academic rank, disciplinary background, and institutional context. The sample included scholars at various career stages, from early-career researchers to full professors, representing a broad spectrum of disciplines. This heterogeneity enabled a multidimensional perspective on academic motivations and the prestige economy within different organisational and epistemic environments.

The methodological rule of triangulation was applied in the research (Denzin & Lincoln, 2024), which allowed for an intersubjective assessment of the cognitive value of the collected material. In particular, the following methods were employed: researcher triangulation (interviews conducted by two authors) and data triangulation at the individual level (information was collected from unrelated individuals).

Individual in-depth interviews (IDIs) were conducted with eleven academics from public and private higher education institutions in Poland. Participants were purposively selected based on their research and teaching experience, as well as their diversity in age and discipline, to provide a broad range of perspectives on the study topic. The semi-structured interviews included pre-prepared questions that allowed flexibility, and the data were transcribed and analysed using thematic analysis. The sample included a range of positions, from PhD holders to full professors, across various disciplines, ensuring a comprehensive understanding of prestige's impact in different academic contexts. The interviews generated 13 hours of material, which were transcribed and coded by two researchers to ensure reliability. Ethical approval was obtained, and confidentiality was maintained through anonymisation. The coding scheme was developed to capture intrinsic and extrinsic motivations, providing a well-grounded interpretation of the data through the lens of SDT.

3. Research results

Existing quantitative research, such as the OECD and Nature's 2019 global PhD surveys, provides important contextual insights. According to a large-scale international survey, 84% of researchers reported being proud to work in the research community. Nevertheless, only 29% felt secure in pursuing an academic career, highlighting the growing tension between professional autonomy and systemic precarity (OECD, 2023). In an extensive 2020 survey of research culture, one in five early-career researchers (23%) reported feeling pressured by their supervisor to produce research results, highlighting project-related stress in academia (Wellcome Trust, 2020). Similarly, Nature's 2019 global PhD survey revealed that nearly three-quarters of doctoral students (74%) were satisfied with their decision to pursue a PhD – a sign of strong intrinsic motivation – even as over one-third had sought help for anxiety or depression related to their research (Woolston, 2019). Considering these challenges, this analysis focuses on three core categories: autonomy in academic work, scientific competence, and relationships within the academic community. It examines how these factors influence academics' motivations. It provides insights into the interplay between personal identity, structural frameworks, and interpersonal dynamics, revealing the diverse factors that drive academic engagement within the prestige economy.

Ad.1. Autonomy in academic work

a) Academic identity versus organizational identity

Discussions around academics' essence touch on the balance between their individual identity and the identity conferred by their institution. This balance influences their scientific endeavours and public perception, encouraging them to focus on seeking and communicating academic values.

"Evaluating through the lens of organizational identity is significantly easier for some academics." [MPLS]. The central concern is harmonizing academic and organizational identities. The equilibrium between them is crucial for ensuring autonomy, as it significantly impacts how academics perceive and conduct their work.

b) Pursuit of autonomy and self-realization

The intrinsic motivations driving academics include a strong desire for autonomy and self-realization. By choosing academia over other professions, they admit they get intellectual freedom and seek personal fulfilment and recognition that transcends financial rewards. "The accumulated knowledge and experience expand capabilities, allowing one to effectively perform tasks that others, without the necessary knowledge, cannot handle." [MPUSZ]. This sentiment is further reinforced by the notion that accumulated knowledge and experience expand one's development capabilities.

c) Socio-cultural dynamics of academic autonomy

The social, cultural, and structural contexts within which academics operate profoundly influence their professional trajectories and the assessment of their autonomy. Between 2013 and 2023, the EU significantly increased its R&D spending, from 2.08% to 2.22% of GDP, amounting to €381 billion in 2023 alone. Notably, most of this growth was driven by the business sector, whose share rose from 1.33% to 1.47% of GDP (Eurostat, 2024). While this suggests heightened investment in knowledge economies, it also reflects the increasing structural dependency of academic research on market-driven priorities. For researchers, this evolving funding landscape intensifies the tension between pursuing autonomy and the institutional pressure to align with performance-based, externally funded models of knowledge production. "The 'ivory tower academics' concept described someone working in isolation, which used to be acceptable, even if it had a negative connotation. However, today, such an image of an academic who works in isolation and writes their papers is entirely impossible." [FPPW]. The socio-cultural contexts within which academics operate influence their professional trajectories and the assessment of their autonomy. This is evident in the imposition of specific ideological and worldview frameworks in project-based work, where individuals either conform or risk becoming marginalised within the system.

d) Importance of academic institutions and personal engagement

The prestige of HEIs significantly influences the individual standing of academics. However, personal engagement and active contribution are essential for building and sustaining one's academic reputation within the scientific community. "I identify as a professor of a discipline and a university professor. In the business context, this would be akin to employer branding, where the academic culture and traditions of the university are emphasised." [MPLS]. The reputation of esteemed academic institutions significantly enhances the individual standing of scholars. Personal engagement, active contribution, and a steadfast commitment to the institution's values are vital for sustaining and improving one's academic reputation. Academics must align their identity with the ethos of their institutions to maximise their prestige.

Ad.2. Scientific competence

a) Structure and evaluation of academic careers

The framework and evaluation systems within academia are crucial in shaping academics' careers and determining publication outcomes. These systems frequently revolve around project-based work and specific ideological frameworks that they must navigate. This structure is crucial for evaluating academic achievements, publication activities, and adherence to institutional standards. "When it comes to evaluation, I have personally conformed to the prevailing rules at the university. I accept the necessity of evaluating academic achievements, scientific qualities, and publication activities. I do not have much choice as I work at a public university." [FPPW]. The structures and evaluation criteria of academic institutions significantly shape academic careers. Evaluation processes, such as point systems and publication requirements, are designed to provide transparency, but they can also impose constraints that academics must navigate. In many countries, PhD education has expanded rapidly, often supported by performance-based funding formulas that reward universities for the number of

doctorates awarded. The growing number of PhDs awarded—such as a 37% increase in the United States since 2003, a 61% increase in the French-speaking Community of Belgium between 2000 and 2017, and a 260% increase in the Netherlands over the past 30 years—indicates a rising influx of researchers into the academic labor market. In France, for example, the ratio of doctorates awarded to available university and public research positions is approximately 10:1, highlighting a structural imbalance (OECD, 2023). This trend leads to a steady flow of highly qualified individuals competing for an increasing number of short-term academic positions, thereby shaping career trajectories and influencing motivational dynamics in academia.

b) Exclusivity and equal opportunities in science

In scientific competence, ongoing discourse centres on upholding rigorous intellectual standards and fostering equitable developmental opportunities for all researchers. This equilibrium is pivotal in cultivating a competitive yet inclusive academic milieu and profoundly influences academics' motivational dynamics. "There should be equality of opportunity, meaning it should be elite but also egalitarian in providing development opportunities." [MPLS]. Maintaining rigorous intellectual standards remains essential, and ensuring equal development opportunities for all researchers is equally necessary. This approach fosters a competitive but inclusive academic environment.

c) Experience and professional development of academics

Integrating lifelong learning and interpersonal academic relationships drives professional advancement in science. These elements shape an academic's development. "I recognise a snowball effect in the early stages—rigorously writing, attending numerous classes, and completing a doctorate. Later, one begins to weigh the pros and cons, deciding what is valuable and can be cut. This maturity comes with time." [FPUWR]. Academics' professional development reflects an iterative growth process from engagement to mature decision-making based on experience and critical evaluation.

d) Public image of academics and its impact on prestige

The public perception of academics, their communicative abilities, and the significance of publications and public appearances are pivotal in cultivating prestige. "Academic work is primarily about sharing our research findings with our peers. Often, these studies are interdisciplinary, allowing academics from different fields to access them." [FPPW]. Academics believe they must possess excellent knowledge and the ability to communicate it effectively, as this affects their prestige. "The race among researchers has been ongoing for centuries. The process has evolved with networking, altering the pace, scale, and recognition." [MPLS]. Expertise and communication skills are essential for academics as they enhance their professional standing.

Ad. 3. Relationships of the academic community

a) Connections between lecturers and students

Relationships with students are crucial for shaping academic and personal development. Effective mentoring and personal interactions influence educational experiences and the development of motivation for teaching. "I represent the part of higher education that places excellent hope in teaching. Sometimes a single sentence said during a class can be so significant, opening up new thoughts or helping students, that the rest of the class becomes irrelevant." [MPULSF]. Academics engage in various activities throughout their careers, including writing, teaching classes, and pursuing advanced degrees. They gain the maturity to evaluate and refine their actions, focusing on what is most valuable. The key to this process is a service-oriented approach to instruction, with the reflective evaluation of their teaching methods and acceptance of student feedback to improve themselves as educators.

b) Elitism and the role of elites in science

Intellectual, academic elites are recognised as pivotal in maintaining the integrity and prestige of scientific endeavours and inspiring the broader academic culture. "Every society should have social elites for structural and functional reasons. These elites used to form a part of social capital, a goal as important as a strong economy. Well-educated elites with both pragmatic and substantive competencies and ethical ones are crucial, and such ethical competencies are sorely lacking today."

[FPPW]. Intellectual elites in the academic community are essential to setting high ethical standards. Their influence is crucial in maintaining the integrity and prestige of the scholarly enterprise, thereby inspiring a broader academic culture. These elites serve as role models and custodians of intellectual capital, contributing to society's structural and functional needs.

c) Collaboration and institutional connections

Institutional affiliations and international collaborations are crucial for fostering a sense of community and relatedness among academics. Leydesdorff et al. (2017) demonstrate that international cooperation has a positive and statistically significant impact on citation rates. In contrast, the impact of public funding proves to be statistically insignificant. Moreover, openness and international cooperation are strongly correlated with higher citation visibility, according to an OECD (2023) report. These connections facilitate emotional and social support, driving effective partnerships and collaborative research. Connections between academics foster emotional and social bonds, enhancing the effectiveness of partnerships and collaborative research. Positive relationships and comfortable environments drive successful scientific collaborations and generate new research ideas.

d) Ethics, relationships and prestige

Ethical conduct, guided by academic values, and the development of ethical competence are vital to building and maintaining the prestige of academics. Their integrity and ethical behaviour are a cornerstone of their professional reputation. Adherence to high ethical standards is crucial to maintaining the integrity and prestige of the scientific community. The emphasis on respect for knowledge, diversity, and personal culture is essential to promoting the values that distinguish the intellectual elite.

4. Discussion

Integrating prestige into SDT shows how academic prestige affects intrinsic and extrinsic motivations, particularly autonomy, competence, and relatedness. While fulfilling the need for independence enhances motivation, prestige can restrict it by pressuring academics to align with recognised topics. However, it can also provide greater freedom through improved recognition and funding opportunities (Deci & Ryan, 2000; Vallerand, 1997; Schmidt & Langberg, 2007).

Prestigious achievements, such as high-impact publications, significant grants, and esteemed awards, serve as external validation of an academic's skills and expertise, significantly boosting self-confidence and perceived competence, thereby enhancing their motivation to engage further in their field (González-Sauri & Rossello, 2023). However, this focus on external validation might also drive academics to prioritise outcomes more likely to accrue prestige rather than engaging deeply with research for personal and professional growth, potentially leading to a misalignment of intrinsic motivation and actual activities (Ryan & Deci, 2000). Also, Kotera et al. (2021) noticed that pursuing prestigious "external experiences" is distinct from true intrinsic motivation stemming from authentic personal interests.

Academics with high prestige are often sought after for collaborations, enhancing their sense of belonging and connectedness within the academic community. Also, Bozeman and Gaughan (2011) found that prestige is positively associated with faculty members' sense of professional connectedness and integration within their institution. However, an excessive focus on prestige can engender competitive rather than collaborative relationships, potentially undermining the genuine connections that foster a supportive academic environment (Deci & Ryan, 1985).

Incorporating prestige into SDT reveals that academic motivations are influenced not only by fulfilling basic psychological needs but also by prestige-related rewards. Prestige can reinforce socioeconomic advantages, with scholars from higher socioeconomic backgrounds more likely to attend prestigious universities (Morgan et al., 2022), which explains why academics may pursue prestigious outcomes even if they do not align with their intrinsic needs (Lamont, 2009). This revised

framework provides a nuanced understanding of how prestige can lead academics to compromise autonomy or relatedness.

Conclusions

In contemporary academia, the pursuit of knowledge is closely entwined with the pursuit of prestige. Scholars are driven not only by intrinsic curiosity and a passion for discovery but also by the desire for recognition, influence, and status within the scientific community. This dynamic interplay between fundamental psychological motivations and the reward of prestige forms the backdrop of the present study. We set out to examine this interplay through the lens of SDT (SDT), a framework that traditionally emphasizes autonomy, competence, and relatedness as the key needs fuelling motivation. By revisiting SDT in the context of the prestige economy of science, our goal was to understand how the quest for prestige affects academic motivation in practical and profound ways. The Polish academic context provided a compelling setting for this inquiry, as Poland's universities and researchers increasingly navigate both global benchmarks and local expectations of excellence. Within this setting, our study asked how prestige interweaves with academics' sense of autonomy, their drive for competence, and the bonds of collegial relatedness.

To pursue these questions, we adopted a qualitative, interpretative approach, conducting in-depth interviews with eleven Polish academics from diverse disciplines and career stages. This method allowed us to gather rich, nuanced accounts of personal experience with prestige in academic life. Our analysis of the interview data, supported by thematic coding and cross-examination among researchers, uncovered several key patterns. The findings reveal that prestige plays a nuanced dual role in academic motivation. On one hand, the attainment of prestigious milestones, such as publishing in high-impact journals, winning respected awards, or securing positions at elite institutions, bolsters an academic's sense of competence by affirming their expertise, and it strengthens relatedness by opening doors to influential professional networks and collaborations. Prestige, in this positive light, provides validation and can energize scholars, reinforcing their connection to the academic community. On the other hand, the pull of prestige can come at the expense of autonomy. Many participants voiced that the pressure to align with prestige-driven norms, focusing on topics, methods, or outcomes most likely to win recognition, sometimes constrained their freedom to pursue personally meaningful or innovative lines of inquiry. In short, while prestige can validate and motivate by providing symbolic and tangible rewards, it can also subtly redirect academic effort away from intrinsic interests, creating tensions between what is academically rewarding and what is personally fulfilling. Notably, our interviews also hinted that these effects are not uniform: for instance, prestige considerations often influence how scholars choose collaborators or mentors, and some respondents observed that traditional prestige systems can unintentionally reinforce inequalities (such as gender disparities in recognition and opportunities). These insights underscore that prestige's influence is complex, capable of both elevating academic work and introducing new challenges to intellectual autonomy and equity.

The foremost theoretical contribution of this study is the proposal of a prestige-augmented SDT model that explicitly integrates the concept of prestige (as a form of symbolic capital) with the core psychological needs of autonomy, competence, and relatedness. This integration represents a novel expansion of SDT, extending its explanatory power by accounting for socio-cultural forces that drive academic behaviour. In traditional SDT, motivation is understood largely in terms of internal needs and values versus external incentives; our expanded model demonstrates that prestige blurs the line between these categories. Prestige can function simultaneously as an intrinsic motivator (deeply internalized as part of one's identity and values, where recognition is personally gratifying) and as an extrinsic incentive (external rewards and status). By incorporating prestige into the motivational framework, we highlight how symbolic rewards and status considerations intersect with basic psychological needs. This enriched perspective advances theory by revealing a more holistic picture of academic motivation—one that acknowledges not just the psychological, but also the sociological

economy in which academics operate. It sheds light on why highly capable and autonomous scholars might still chase external marks of distinction, and conversely, how the structure of prestige in academia can affect one's sense of competence and belonging. In sum, the study offers a fresh theoretical lens for understanding academic motivation, bridging SDT with the prestige economy of science and opening up new lines of inquiry about how esteem and reputation intertwine with the motivational processes of academics. Beyond theoretical insights, our findings carry practical implications for higher education policy and academic leadership. University administrators, research funders, and department leaders should be cognizant of the double-edged nature of prestige in academic life. On one side, carefully designed recognition and reward systems can harness the positive power of prestige: acknowledging excellent work, fostering healthy competition, and building vibrant scholarly communities. For example, transparent and fair criteria for promotions, awards, and grants can validate genuine achievement and enhance academics' feelings of competence and relatedness. On the other side, policymakers and leaders must guard against incentive structures that inadvertently stifle autonomy or encourage perverse outcomes. If too much emphasis is placed on a narrow set of prestige indicators—such as only counting publications in a few top-tier journals or obsessing over university rankings—academics may feel pressured to “play it safe” or conform to established prestige norms, potentially at the cost of creativity and intellectual risk-taking. To counterbalance this, institutions should develop policies that support intrinsic motivation and intellectual diversity. This could include broadening the definition of academic success beyond traditional prestige metrics: valuing impactful teaching, openscience practices, interdisciplinary collaboration, or contributions to society that may not come with immediate accolades. Academic leadership should also promote a culture of equity and inclusion in the prestige economy. Our study's participants pointed out that access to prestige is not always equal, factors like gender, age, or institutional resources can influence who reaps the rewards. Thus, leaders should strive to create mentorship programs, funding opportunities, and evaluation processes that level the playing field, ensuring that talented researchers from all backgrounds have pathways to earn recognition. In practical terms, the lesson is clear: higher education institutions need to strike a balance by celebrating excellence and encouraging ambition, while also safeguarding the autonomy of scholars and the ethical, collaborative spirit of research.

While this study offers important insights, it is not without limitations. First, the research was conducted with a relatively small sample of academics (eleven interviewees) and is confined to a single national context – Poland. The qualitative, in-depth approach allowed us to explore experiences and perceptions in detail, but it also means that our findings may not be readily generalizable to all academics or to other countries' higher education systems. The Polish academic environment has its own historical, cultural, and organizational nuances; for instance, local funding structures, evaluation criteria, and academic traditions could shape how prestige is experienced. Readers should therefore be cautious in extending our conclusions to different settings without further evidence. Second, as a qualitative study relying on self-reported experiences, there is the possibility of bias in what participants chose to share or emphasize. We mitigated this through careful triangulation and by selecting a diverse sample, but some dimensions of the prestige-motivation interplay might remain underexplored or differ in other contexts. Additionally, our focus on the university sector in a specific period offers a snapshot in time. Academic norms and policies evolve what holds true in the current prestige climate may shift with new generations of scholars or changes in the academic labour market. In light of these factors, the contributions of this work should be viewed as exploratory and hypothesis-generating. They map out a conceptual territory that future research can further chart, rather than a definitive, one-size-fits-all model for all of academia.

Building on the foundation laid here, we see several avenues for future research. Empirical studies with larger and more varied samples are needed to test the prestige-augmented SDT model across different contexts. Quantitative research, for example, could measure the impact of prestige-related factors (like institutional reputation or citation-based metrics of individual prestige) on indicators of

motivation, performance, or well-being among academics in multiple countries. Such studies would help determine whether the dynamics observed in Poland occur similarly elsewhere or if cultural and systemic differences alter the prestige-motivation relationship. Cross-national comparisons, perhaps between Polish academics and those in Western European or North American systems, could be particularly illuminating. It would also be valuable to examine different academic disciplines and career stages in future work. The role of prestige might be more pronounced in research-intensive fields or at certain career points (for instance, during the race for tenure vs. later in a career); thus, comparative studies across fields (natural sciences, social sciences, humanities) or longitudinal studies following academics over time could yield deeper insights. Further qualitative research in other national contexts—especially in emerging higher education systems or under-represented regions—would also extend the understanding of how local prestige economies operate. Finally, an important direction for future inquiry is the development and testing of interventions or policy changes inspired by our findings. Researchers could experiment with new incentive structures or support programs at universities to see if tweaking the prestige economy (for example, by recognizing team science, community engagement, or open-access publishing) can maintain high motivation and performance while reducing negative pressures. Such practical experiments, coupled with continued theoretical refinement, will ultimately help academic communities worldwide to foster an environment where the healthy pursuit of prestige aligns with, rather than undermines, the intrinsic joy of scholarly work.

Author Contributions: L.S.: Conceptualization of the study; overall coordination of the project; development of the initial draft of the manuscript; supervision of the structure and coherence of the paper; J.D.: Investigation; conducting the research; development of the conceptual model; writing – final editing; language editing of the manuscript; S.P.: Co-development of the conceptual model; substantive validation of the manuscript; verification of theoretical accuracy; language editing; R.S.: Technical evaluation; preparation and formatting of the manuscript; editorial support.

Funding: The authors declare that no funding was received for the conduct of this research or the preparation of this article.

Data Availability Statement: The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest: The authors affirm no conflict of interest.

Reference

1. Amabile, T. M., Hill, K. G., Hennessey, B. A., & Tighe, E. M. (1994). The work preference inventory: Assessing intrinsic and extrinsic motivational orientations. *Journal of Personality and Social Psychology*, 66(5), 950–967. <https://doi.org/10.1037/0022-3514.66.5.950>.
2. Anderson, M. S., Martinson, B. C., & De Vries, R. (2007). Normative dissonance in science: Results from a national survey of U.S. scientists. *Journal of Empirical Research on Human Research Ethics*, 2(4), 3–14. <https://doi.org/10.1525/jer.2007.2.4.3>.
3. Blackmore, P. (2015). *Prestige in Academic Life. Excellence and Exclusion*. London: Routledge. <https://doi.org/10.4324/9781315715780>.
4. Bourdieu, P. (1986). The forms of capital. In J. G. Richardson (Ed.), *Handbook of Theory and Research for the Sociology of Education* (pp. 241–258). Greenwood.
5. Bozeman, B., & Gaughan, M. (2011). Job Satisfaction among University Faculty: Individual, Work, and Institutional Determinants. *The Journal of Higher Education*, 82(2), 154–186. <https://doi.org/10.1353/jhe.2011.0011>.
6. Brembs, B., Button, K., & Munafò, M. R. (2013). Deep impact: Unintended consequences of journal rank. *Frontiers in Human Neuroscience*, 7, Article 291. <https://doi.org/10.3389/fnhum.2013.00291>.
7. Chirkov, V., Ryan, R. M., Kim, Y., & Kaplan, U. (2003). Differentiating autonomy from individualism and independence: A self-determination theory perspective on internalizing

- cultural orientations and well-being. *Journal of Personality and Social Psychology*, 84(1), 97–110 <https://doi.org/10.1037/0022-3514.84.1.97>.
8. Cummings, J. N., & Kiesler, S. (2008). Collaborative research across disciplinary and organizational boundaries. In S. Kiesler (Ed.), *Scientific collaboration on the internet* (pp. 99–118). MIT Press. <https://doi.org/10.1177/030612705055535>.
 9. Deci, E. L., & Ryan, R. M. (2000). The "what" and "why" of goal pursuits: Human needs and the self-determination of behavior. *Psychological Inquiry*, 11(4), 227–268. https://doi.org/10.1207/S15327965PLI1104_01.
 10. Deci, E. L., Vallerand, R. J., Pelletier, L. G., & Ryan, R. M. (1991). Motivation and education: The self-determination perspective. *Educational Psychologist*, 26(3-4), 325–346. https://doi.org/10.1207/s15326985ep2603&4_6.
 11. Denzin, N. K., & Lincoln, Y. S. (Eds.). (2024). *The SAGE Handbook of Qualitative Research* (5th ed.). Sage. <https://doi.org/10.4135/9781529770278>.
 12. Dziedzic, J., & Sułkowski, L. (2023). The Role of the Scientist's Personal Brand in the Reflexive Construction of Organizational Identity. *Discourses on Culture*, 20(1), 199–228. <https://doi.org/10.2478/doc-2023-0016>.
 13. English, J. F. (2005). *The economy of prestige: Prizes, awards, and the circulation of cultural value*. Harvard University Press. <https://doi.org/10.1007/s10824-006-9003-x>.
 14. Eurostat. (2024). R&D expenditure – Statistics Explained. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=R%26D_expenditure.
 15. Gao, Z., & Yuan, R. (2024). Understanding professional vulnerability in an era of performativity: Experiences of EFL academics in mainland China. *Teaching in Higher Education*, 29(1), 318–333. <https://doi.org/10.1080/13562517.2021.1989577>.
 16. González-Sauri, M., & Rossello, G. (2023). The Role of Early-Career University Prestige Stratification on the Future Academic Performance of Scholars. *Research in Higher Education*, 64, 58–94. <https://doi.org/10.1007/s11162-022-09679-7>.
 17. Hermanowicz, J. C. (1998). *The stars are not enough: Scientists—their passions and professions*. University of Chicago Press.
 18. Jenö, L. M., Diseth, Å., & Danielsen, A. G. (2018). A prospective investigation of students' academic achievement and dropout in higher education: A self-determination theory approach. *Educational Psychology*, 37(9), 1027–1049. <https://doi.org/10.1080/01443410.2018.1502412>.
 19. Kieser, A., & Leiner, L. (2009). Why the rigour-relevance gap in management research is unbridgeable. *Journal of Management Studies*, 46(3), 516–533. <https://doi.org/10.1111/j.1467-6486.2009.00831.x>.
 20. Klahn Acuña, B., & Male, T. (2024). Toxic leadership and academics' work engagement in higher education: A cross-sectional study from Chile. *Educational Management Administration & Leadership*, 52(3), 757–773. <https://doi.org/10.1177/17411432221084474>.
 21. Kotera, Y., Conway, E., & Green, P. (2021). Construction And Factorial Validation of a Short Version of the Academic Motivation Scale. *British Journal of Guidance & Counselling*, 51(2), 274–283. <https://doi.org/10.1080/03069885.2021.1903387>.
 22. Kwiek, M. (2021). The prestige economy of higher education journals: A quantitative approach. *Higher Education*, 81(3), 493–519. <https://doi.org/10.1007/s10734-020-00553-y>.
 23. Lamont, M. (2009). *How professors think: Inside the curious world of academic judgment*. Harvard University Press.
 24. Lamont, M. (2012). Toward a comparative sociology of valuation and evaluation. *Annual Review of Sociology*, 38, 201–221. <https://doi.org/10.1146/annurev-soc-070308-120022>.
 25. Li, L., & Tao, J. (2025). Academics' identity struggles and professional agency in the transition to teaching in a professional master's degree programme. *Higher Education Research & Development*, 1–17. <https://doi.org/10.1080/07294360.2025.2503825>.

26. Leydesdorff, L., Bornmann, L., & Wagner, C. S. (2017). The relative influences of government funding and international collaboration on citation impact. arXiv preprint arXiv:1701.08311.
27. Long, J. S. (2001). From scarcity to visibility: Gender differences in the careers of doctoral scientists and engineers. National Academy Press.
28. Merton, R. K. (1973). The sociology of science: Theoretical and empirical investigations. University of Chicago Press.
29. Morgan, A.C., LaBerge, N., Larremore, D.B., Galesic, M., Brand, J. E., & Clauset, A. (2022). Socioeconomic Roots of Academic Faculty. *Nature Human Behaviour*, 6, 1625–1633. <https://doi.org/10.1038/s41562-022-01425-4>.
30. Niemiec, C. P., & Ryan, R. M. (2009). Autonomy, Competence, and Relatedness in the Classroom Applying Self-Determination Theory to Educational Practice. *Theory and Research in Education*, 7, 133–144. <https://doi.org/10.1177/1477878509104318>.
31. OECD. (2023). OECD Science, Technology and Innovation Outlook 2023: Enabling Transitions in Times of Disruption. OECD Publishing.
32. Olsen, A., & Mason, E. (2023). Perceptions of Autonomy: Differential Job Satisfaction for General and Special Educators Using a Nationally Representative Dataset. *Teaching and Teacher Education*, 123, Article 103999. <https://doi.org/10.1016/j.tate.2022.103999>.
33. Przytuła, S., Sułkowski, Ł., & Kulikowski, K. (2024). Human resource management in higher education institutions: an international perspective. Routledge.
34. Ross, P. M., Scanes, E., & Locke, W. (2023). Stress adaptation and resilience of academics in higher education. *Asia Pacific Education Review*, 25(1), 829–849. <https://doi.org/10.1007/s12564-023-09829-1>.
35. Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist*, 55(1), 68–78. <https://doi.org/10.1037/0003-066X.55.1.68>.
36. Ryan, R. M., & Deci, E. L. (2001). On happiness and human potentials: A review of research on hedonic and eudaimonic well-being. *Annual Review of Psychology*, 52, 141–166. <https://doi.org/10.1146/annurev.psych.52.1.141>.
37. Schmidt, E. K., & Langberg, K. (2007). Academic Autonomy in a Rapidly Changing Higher Education Framework: Academia on the Procrustean Bed? *European Education*, 39(4), 80–94. <https://doi.org/10.2753/EUE1056-4934390406>.
38. Shengyao, Y., Jenatabadi, H. S., Mengshi, Y., Minqin, C., Xuefen, L., & Mustafa, Z. (2024). Academic resilience, self-efficacy, and motivation: The role of parenting style. *Scientific Reports*, 14, Article 55530. <https://doi.org/10.1038/s41598-024-55530-7>.
39. Sheldon, K. M., & Krieger, L. S. (2007). Understanding the adverse effects of legal education on law students: A longitudinal test of self-determination theory. *Personality and Social Psychology Bulletin*, 33(6), 883–897. <https://doi.org/10.1177/0146167207301014>.
40. Shorey, S., Chua, C. M. S., & Yap Seng, C. (2023). Turbulent academic journey of female academics: a meta-synthesis. *International Journal of Inclusive Education*, 29(6), 863–883. <https://doi.org/10.1080/13603116.2023.2227862>.
41. Sułkowski, Ł., & Dziedzic, J. (2023). Challenges of Academic Ethos: The Scientific Community's Response to the Ostracism of Russian Scientists Following the Invasion of Ukraine. *Journal of Intercultural Management*, 15(1), 147–177. <https://doi.org/10.2478/joim-2023-0021>.
42. Sułkowski, Ł. (2023). Managing the digital university: paradigms, leadership, and organization (p. 299). Taylor & Francis.
43. Taylor, I. M., Ntoumanis, N., Standage, M., & Spray, C. M. (2014). Motivational predictors of physical education students' effort, exercise intentions, and leisure-time physical activity: A multilevel linear growth analysis. *Journal of Sport and Exercise Psychology*, 36(1), 99–120. <https://doi.org/10.1123/jsep.32.1.99>.

44. Vallerand, R. J. (1997). Toward a hierarchical model of intrinsic and extrinsic motivation. *Advances in Experimental Social Psychology*, 29, 271–360. [https://doi.org/10.1016/S0065-2601\(08\)60019-2](https://doi.org/10.1016/S0065-2601(08)60019-2).
45. Van den Brink, M., & Benschop, Y. (2012). Gender practices in the construction of academic excellence: Sheep with five legs. *Organization*, 19(4), 507–524. <https://doi.org/10.1177/135050841141429>.
46. Wellcome Trust. (2020). What researchers think about the culture they work in. <https://wellcome.org/reports/what-researchers-think-about-research-culture>.
47. Walsh, J. P., & Maloney, N. G. (2007). Collaboration structure, communication media, and problems in scientific work teams. *Journal of Computer-Mediated Communication*, 12(2), Article 19. <https://doi.org/10.1111/j.1083-6101.2007.00346.x>.
48. Willmott, H. (2011). Journal list fetishism and the perversion of scholarship: Reactivity and the ABS list. *Organization*, 18(4), 429–442. <https://doi.org/10.2139/ssrn.1753627>.
49. Woolston, C. (2019, November 13). PhDs: the tortuous truth. *Nature*. <https://www.nature.com/articles/d41586-019-03459-7>.
50. Zuckerman, H. (1977). *Scientific elite: Nobel laureates in the United States*. Transaction Publishers.

The Moderating Role of Urbanisation in the Environmental Impact of Economic Complexity and Capital Formation: Evidence from OECD Countries

Kemal Erkisi¹

¹ Antalya Bilim University, Department of Economics, Antalya, Türkiye

ORCID: 0000-0001-7197-8768

e-mail: kemal.erkisi@antalya.edu.tr

Abstract

Environmental degradation remains a pressing challenge for high-income countries as they strive to balance economic growth with ecological sustainability. While previous studies have examined various drivers of environmental outcomes, the interplay between economic complexity, capital formation, and energy use has received limited attention. This study investigates how these factors influenced ecosystem vitality in high-income countries over the period of 2000–2022. Drawing on Ecological Modernisation Theory and the Environmental Kuznets Curve framework, this study employs four panel data estimation methods, Panel-Corrected Standard Errors, Driscoll–Kraay Estimators, Poisson Pseudo-Maximum Likelihood, and Feasible Generalised Least Squares, to address cross-sectional dependence, heteroskedasticity, and potential non-linearities. The analysis reveals three key findings. First, while economic complexity improves ecosystem vitality, this benefit weakens substantially in highly urbanised contexts, indicating diminishing returns to knowledge spillovers in dense urban environments. Second, urbanisation significantly reduces the negative environmental impacts of capital accumulation, suggesting that urban agglomeration enables more sustainable infrastructure deployment. Third, the urbanisation–environment relationship follows an inverted U-shape, with environmental pressures peaking at intermediate development stages before improving in advanced urban systems. Additionally, renewable energy adoption consistently improves ecosystem vitality, whereas energy intensity exerts negative effects, highlighting the urgency of comprehensive energy transition strategies. These findings demonstrate that urbanisation acts not as a uniform force, but as a dynamic variable requiring spatially differentiated strategies: governance and infrastructure optimisation in dense urban cores, complexity-driven innovation in peri-urban regions, and energy-intensity regulations across all development stages. These findings point to an integrated policy framework that addresses (1) density-sensitive economic complexity, (2) circular infrastructure investment, (3) institutional capacity building, and (4) multi-scalar energy transitions to better align urban development with environmental sustainability.

Key words

urbanisation, economic complexity, ecosystem vitality, energy intensity, renewable energy.

Cite as:

Erkisi, K. (2025). The Moderating Role of Urbanisation in the Environmental Impact of Economic Complexity and Capital Formation: Evidence from OECD Countries. *Forum Scientiae Oeconomia*, 13(3), 68–88. https://doi.org/10.23762/FSO_V OL13_NO3_3

Received: 2 June 2025

Revised: 9 September 2025

Accepted: 25 September 2025



Copyright: © 2025 by the authors. For open-access publication within the terms and conditions of the Creative Commons Attribution (CC BY) licence (<https://creativecommons.org/licenses/by/4.0/>).

Introduction

Urbanisation has emerged as one of the most powerful forces shaping environmental sustainability in the 21st century. Beyond physical and spatial transformation, it has the potential to restructure economic systems, energy frameworks, and natural resource use (Zou et al., 2022; Voukkali et al., 2024). Particularly in advanced economies, urban growth not only drives economic expansion but

also transforms environmental outcomes through knowledge-intensive production, infrastructure investments, and the diffusion of eco-friendly technologies. Recent studies have demonstrated that rapid urbanisation significantly impacts ecosystem service values, with population density and economic growth being key factors influencing these services (Liu et al., 2020). However, these positive effects are not universal. Unplanned and rapid urbanisation can lead to increased air and water pollution, habitat destruction, and higher carbon emissions (McGranahan et al., 2007; Zhang et al., 2022). Thus, the environmental consequences of urbanisation depend not only on its scale but also on its quality and the structure of accompanying economic systems.

Recent research highlights that indicators such as economic complexity, which reflect the knowledge and technological intensity of a country's production structure, play a key role in determining environmental outcomes (Hidalgo & Hausmann, 2009; Mealy & Teytelboym, 2022). Countries with higher economic complexity are believed to possess the potential to enhance environmental sustainability through high-value-added and resource-efficient production processes (Romero & Gramkow, 2021; Balsalobre-Lorente et al., 2023). Further evidence suggests that advancements in economic complexity contribute to fostering sustainable environmental practices by facilitating cleaner production technologies and innovation-driven growth (Hassan et al., 2023; Salvati & Carlucci, 2020). However, the relationship is not necessarily linear. In lower- and middle-income countries, rising complexity is often accompanied by industrial expansion and the growth of energy-intensive sectors, which in turn accelerates environmental degradation (Aluko et al., 2023; Doğan et al., 2019). Therefore, factors such as the sectoral structure of production and the composition of energy use play a crucial role in shaping the environmental impact of economic complexity.

In this regard, urbanisation should not be treated solely as an independent variable but rather as a moderator that conditions the environmental effects of structural factors such as economic complexity, capital formation, and energy use (Mol & Spaargaren, 2000; Chang et al., 2024). While extensive research has explored the direct environmental impacts of urbanisation, far less attention has been given to how urban settings interact with other structural drivers. Much of the existing literature examines the relationship between economic complexity and environmental performance within a linear and isolated framework (Romero & Gramkow, 2021; Boleti et al., 2021; Doğan et al., 2019), often neglecting the potential moderating role of spatial structures such as urbanisation. Similarly, although the environmental effects of capital formation and energy use are well-documented (Prakash & Sethi, 2023; Liang et al., 2024), there is still limited empirical understanding of how urbanisation may moderate these influences. Recent studies (Prakash & Sethi, 2023; Liang et al., 2024) reinforce the notion that fixed capital formation and energy consumption generally intensify carbon emissions, underscoring the need for integrated green infrastructure planning in urban environments. As is stressed here, while previous research has highlighted these drivers individually, there is a critical gap in understanding how urbanisation interacts with economic complexity and resource intensity in shaping environmental outcomes. Most existing models overlook the spatial–demographic context, thereby underestimating structural heterogeneity across high-income countries. This study addresses this empirical and theoretical gap by conceptualising urbanisation not merely as a background condition, but as a dynamic moderator of structural–environmental linkages. Addressing this gap is particularly crucial for formulating policy strategies aligned with the Sustainable Development Goals (SDGs). Considering the inherent advantages of urban areas, such as fostering knowledge creation, accelerating technological diffusion, and supporting advanced infrastructure, there is a strong theoretical and practical rationale for examining the moderating role of urbanisation through both conceptual frameworks and empirical analysis.

Building on this rationale, this study constructs a theoretical framework inspired by the extended growth model of Mankiw et al. (1992), integrating urbanisation and economic complexity as additional structural variables. Drawing on the innovation-oriented sustainability perspective of Ecological Modernisation Theory and the nonlinearity hypothesis of the Environmental Kuznets

Curve (EKC), the model posits that environmental improvement can be actively achieved through technological progress, institutional reform, and social innovation (Mol & Spaargaren, 2000). In this context, urban settings offer transformative potential through concentrated infrastructure, knowledge flows, and governance mechanisms. Meanwhile, the EKC framework suggests that environmental pressures may initially worsen but later improve as economies reach higher development thresholds. This study investigates whether urbanisation follows a similar nonlinear pattern in its impact on ecosystem outcomes.

Using panel data for OECD countries from 1995 to 2022, the model tests how urbanization moderates the environmental effects of both economic complexity and capital formation. It incorporates interaction terms and quadratic specifications to capture threshold effects. Additionally, the role of energy intensity and renewable energy use is considered to evaluate how shifts in energy composition affect environmental performance. The empirical analysis employs multiple robust estimation techniques to address methodological challenges such as cross-sectional dependence, heteroskedasticity, autocorrelation, and slope heterogeneity.

The study aims to systematically investigate how urbanization moderates the environmental effects of economic complexity and capital accumulation. It seeks to answer the following key questions: (1) Do the environmental benefits of economic complexity diminish as urban density increases? (2) Does urbanization play a mitigating role in the ecological costs of capital formation? (3) Does the urbanization-environment relationship follow a nonlinear pattern? The findings are expected to offer both theoretical insights and practical implications for sustainable urban policy design.

1. Literature review

Urbanization, while offering extensive opportunities in terms of economic growth, infrastructure development, and access to technology, also presents multidimensional challenges to environmental sustainability. Particularly in contexts of rapid and unplanned urban expansion, numerous studies have identified increasing air and water pollution, land degradation, and biodiversity loss as common environmental consequences (McGranahan et al., 2007; Zhang et al., 2022; Voukkali et al., 2024). Recent studies further highlight that rapid urbanization, if not accompanied by adequate green infrastructure planning, can significantly deteriorate environmental quality (Kusiyah et al., 2024). Moreover, fostering urban resilience strategies has been recognized as an essential pathway to mitigate these environmental pressures (Revi et al., 2014), while coordinated urban cluster development offers additional opportunities for enhancing environmental protection (Xu & Luo, 2025). Recent evidence further suggests that spatial expansion and economic intensification within urban areas can produce heterogeneous effects on pollution dynamics, underscoring the multidimensional nature of urban environmental impacts (Wei et al., 2025). In addition, Urbanization-driven transformations are found to significantly alter regional carbon cycles and biogeochemical processes, thereby intensifying global environmental pressures (Shurpali, 2023; Churkina, 2016). However, this relationship is not linear. In advanced economies, urban forms that have reached certain thresholds of institutional capacity and environmental regulation are shown to contribute positively to ecosystem health (Stern, 2017; Cao et al., 2025).

This transformation is largely interpreted through the lens of Ecological Modernization Theory (EMT), which argues that environmental issues are not inevitable byproducts of economic growth but can be addressed through technological innovation, institutional reform, and social learning (Mol & Spaargaren, 2000). Urban areas serve as fertile grounds for this transformation, offering advantages such as high population density, enhanced knowledge exchange, technological diffusion, and economies of scale (Zou et al., 2022; Chang et al., 2024). Additionally, cities often concentrate governance institutions and monitoring mechanisms, making the enforcement of environmental policies more feasible.

Nevertheless, the outcomes envisioned by EMT are not universally achieved. In many low-income or institutionally weak countries, urbanization tends to be characterized by informal settlements, inadequate infrastructure, and fragile governance structures, which amplify environmental pressures rather than alleviate them (Latief et al., 2022; Das et al., 2021; Adebayo & Kirikkaleli, 2022). Thus, the environmental consequences of urbanization are highly contextual, shaped by income levels, governance quality, technological capacity, and spatial planning.

Recent literature suggests that the impact of urbanization on environmental quality may follow an inverted-U trajectory, whereby environmental degradation increases up to a certain threshold of urban development, beyond which environmental indicators begin to improve (Cheng et al., 2023; Liang et al., 2024). This conceptualization, known as the Urban Environmental Kuznets Curve (UEKC), implies that not only the extent but also the quality and form of urbanization determine its environmental implications. For instance, countries with similar urbanization rates may produce divergent environmental outcomes depending on their institutional effectiveness.

Economic complexity, defined as the diversity and knowledge intensity of a country's productive capabilities, has also emerged as a significant determinant of environmental outcomes (Hidalgo & Hausmann, 2009). Complex economies are expected to support sustainable development by producing high value-added goods using cleaner, knowledge-based technologies (Mealy & Teytelboym, 2022). Recent empirical studies increasingly examine how economic complexity and urban dynamics influence environmental outcomes (Bashir et al., 2022; Balsalobre-Lorente et al., 2023; Chang et al., 2024).

Theoretically, more complex economies are assumed to reduce environmental harm due to their capacity for technological innovation, resource efficiency, and alignment with stringent environmental standards (Romero & Gramkow, 2021; Boleti et al., 2021). Indeed, countries that have invested in green technologies, recycling systems, and environmental innovation tend to display a positive association between economic complexity and ecological indicators (Balsalobre-Lorente et al., 2023; Bashir et al., 2022; Pata, 2021).

However, this relationship is not universally consistent. In low- and middle-income countries, increased complexity may coincide with industrial expansion in energy-intensive sectors, thereby exacerbating carbon emissions and resource depletion (Doğan et al., 2019; Aluko et al., 2023; Khezri et al., 2022). The sectoral composition of complexity becomes crucial in this regard. If complexity is driven by environmentally harmful industries, its sustainability benefits may be limited or even reversed (Degirmenci et al., 2024; Adebayo & Kirikkaleli, 2022).

Moreover, the environmental impact of economic complexity is closely tied to a country's energy profile. Economies that combine high complexity with a renewable energy base can limit their ecological footprint, whereas those reliant on fossil fuels may experience diminished sustainability gains (Khezri et al., 2022; Bashir et al., 2022; Balsalobre-Lorente et al., 2023). Therefore, aligning energy transition policies with economic upgrading is essential.

Urbanization, traditionally treated as an independent factor in environmental research, is increasingly recognized as a moderating variable that shapes how structural drivers like economic complexity, capital formation, and energy use translate into environmental outcomes (Mol & Spaargaren, 2000; Zou et al., 2022; Chang et al., 2024). Cities act not only as centers of production and consumption but also as transformative systems that mediate innovation, infrastructure investment, and governance (Balland et al., 2020; Lapatinas et al., 2022; Gomez-Lievano & Patterson-Lomba, 2021). Recent studies further highlight that the internal complexity of urban systems significantly influences environmental trajectories, particularly by shaping resource flows and technological diffusion patterns (Salvati & Carlucci, 2020).

In highly urbanized environments, knowledge-intensive activities are more likely to flourish, thereby amplifying the environmental gains of economic complexity. Yet, without adequate infrastructure or planning, such gains may be eroded by congestion, pollution, and overconsumption of resources (Di Clemente et al., 2021; Fritz & Manduca, 2021). The same holds for capital

investments: while green infrastructure in dense cities may yield positive outcomes, uncoordinated capital formation in low-density regions can fragment ecosystems and increase carbon intensity (OECD, 2023; Radoine et al., 2022).

Energy consumption patterns are also shaped by urban form. Centralized heating systems, public transport networks, and clean energy infrastructure can reduce energy intensity in well-planned urban areas (Stern, 2004; Burger et al., 2019). Conversely, urban sprawl and inadequate energy governance may result in high fossil fuel dependency and negative ecological effects (Degirmenci et al., 2024; Wang & Wang, 2024; Kwilinski et al., 2023). Recent empirical evidence highlights that rapid urbanization, when coupled with inefficient energy systems, significantly intensifies environmental degradation by increasing energy intensity and accelerating carbon emissions (Onifade & Alola, 2023; Franco et al., 2017).

Taken together, urbanization operates not only as a direct environmental driver but also as a potential moderator that reshapes the influence of structural factors on environmental outcomes. Although prior studies have examined the environmental impacts of urbanization within broader sustainability frameworks (Chang et al., 2024; Balsalobre-Lorente et al., 2023; Bashir et al., 2022), explicit empirical modeling of urbanization as a moderating variable remains relatively scarce.

In this context, the current study aims to bridge the theoretical and empirical gap by analyzing how urbanization modifies the effects of economic complexity, capital formation, and energy intensity on ecosystem vitality. Using a comprehensive OECD panel dataset spanning 1995–2022, the study applies interaction modeling to assess not only direct relationships but also conditional effects.

The policy implications are manifold. Environmental and development strategies should not focus solely on enhancing technological sophistication or capital accumulation. Instead, they must be embedded within spatial and institutional contexts that enable sustainability. Promoting compact, knowledge-based urbanization, investing in clean infrastructure, and encouraging renewable energy transitions are not only environmental imperatives but also essential components of resilient economic systems.

2. Methodology

2.1 Theoretical Model

The model begins with an extended production function that incorporates economic complexity as a distinct factor of production. Drawing from endogenous growth theory (Mankiw et al., 1992), we express total output (Y) as:

$$Y = A \cdot K^\alpha \cdot L^\beta \cdot EC^\gamma \quad (1)$$

This specification diverges from traditional Cobb-Douglas formulations by explicitly including economic complexity (EC), which captures the knowledge intensity of production. The exponent γ measures how EC augments output independently of capital and labor. Total factor productivity (A) here subsumes not just technology but also institutional factors that vary across urban environments.

Transitioning from production to environmental impacts, the model links economic output to energy demand through a linear dependence:

$$E = \theta \cdot Y \quad (2)$$

Energy consumption (E) scales with output, where θ represents energy intensity. This coefficient varies across economies based on their sectoral composition and technological sophistication – for instance, service-dominated high- EC economies typically exhibit lower θ values than manufacturing-intensive systems (Stern, 2004). The environmental consequences of energy use are then mediated by the pollution intensity of the energy mix:

$$D = \vartheta_0 \cdot (1 - RE)^\theta \cdot E \quad (3)$$

Here, D quantifies environmental damage, which depends not just on total energy use but crucially on the renewable energy share (RE). The parameter θ captures diminishing returns to renewables' pollution abatement potential, reflecting real-world constraints in green technology deployment.

Urbanization enters the model through two distinct channels. First, it enhances productivity via agglomeration economies:

$$A = \delta \cdot \ln(U) \quad (4)$$

The logarithmic form reflects decreasing marginal benefits of urban concentration (Duranton & Puga, 2004), where δ measures how urbanization boosts innovation and resource allocation efficiency. However, beyond an optimal threshold (U_0), negative externalities emerge:

$$A = \delta \cdot \ln(U) - (\max(0, U - U_0))^2 \quad (5)$$

This quadratic penalty term accounts for congestion costs and infrastructure strains that characterize over-urbanized regions. The ecosystem vitality (EV) then responds to both current and legacy environmental damage:

$$EV_t = \Omega - \lambda \cdot [(1 - \eta) \cdot D_{t-1} + D_t] \quad (6)$$

Where Ω represents the baseline carrying capacity of urban ecosystems, while η quantifies their recovery rate from past damage D_{t-1} . The final specification incorporates urban form's impact:

$$EV_t = \Omega - \lambda \cdot [(1 - \eta) \cdot D_{t-1} + D_t] - \zeta \cdot Spawl \quad (7)$$

The ζ parameter captures how low-density urban expansion (*Sprawl*) compounds environmental stress through habitat fragmentation and increased energy demand for transportation – a critical consideration for OECD cities facing suburbanization pressures. Following standard urban economics literature, we account for urban sprawl effects through the non-linear term of urbanization (UP^2), which captures the density-reducing nature of uncontrolled expansion.

2.2 Variables and Empirical Model

To examine the hypothesized relationships, we construct a panel dataset using standardized metrics for ecosystem vitality, economic complexity, and urbanization dynamics. The panel dataset covers the period 1995-2022 and includes OECD countries. The selected country group provides diversity in terms of both data reliability and advanced production structure and environmental policies. Table 1 details the variable definitions, measurement approaches, and data sources, which prioritize transparency and reproducibility.

Table 1. Variables, definitions, and sources.

Variables	Abrv.	Indicator	Source
Ecosystem vitality	EV	Ecosystem vitality	YEP
Economic complexity	EC	Economic complexity	HGL
Production	FC	Gross fixed capital formation (constant 2015 US\$)	WB
Population	UP	Urban population (% of total population)	WB
Renewable energy	RE	Renewable energy consumption (% of total final energy consumption)	IEA
Energy intensity	EI	Energy intensity	IEA
Interaction term	I_EC	(EC x UP)	AC
Interaction term	I_FC	(FC x UP)	AC

Source: World Bank (2024), World Development Indicators (WB); Yale Center for Environmental Law & Policy (2024), Environmental Performance Index (YEP); Harvard Growth Lab (2024), The Atlas of Economic Complexity (HGL); International Energy Agency (2024), Statistical Review of World Energy (IEA); Author's calculation (AC).

The variable selection in this study is grounded in both ecological economics theory and empirical literature on sustainable development. Ecosystem vitality (EV) serves as the dependent variable, reflecting a nation's capacity to maintain biodiversity, mitigate pollution, and sustainably manage natural resources – a critical metric in OECD countries where urbanization and industrial complexity often strain environmental systems.

Economic complexity (EC), derived from the Hidalgo and Hausmann (2009) framework, captures whether advanced production capabilities correlate with greener technologies or increased resource exploitation. Gross fixed capital formation (FC) controls for the environmental impact of infrastructure investment, as OECD nations balance growth with decarbonization (World Bank, 2024). Urbanization (UP) tests the Environmental Kuznets Curve (EKC) hypothesis, where urban density may initially degrade but later improve ecosystems through economies of scale in green infrastructure (Stern, 2017).

Energy-related variables, renewable consumption (RE) and energy intensity (EI), address the pivotal role of energy transitions in climate policy (IEA, 2024). The interaction terms (EC×UP, FC×UP) examine whether urbanization moderates the ecological effects of economic structure and capital accumulation, a novel contribution to the literature.

Data sources (World Bank, Yale EPI, Harvard Atlas, IEA-Energy Institute) were prioritized for cross-country consistency, with logarithmic transformations applied to non-ratio variables to ensure elasticity interpretations.

The empirical framework begins by specifying the functional relationship between ecosystem vitality (EV) and its determinants, grounded in our theoretical model:

$$EV = f(EC, FC, UP, RE, EI, EC \times UP, FC \times UP) \quad (8)$$

This functional form in Eq.8 captures the direct effects of economic complexity (EC), fixed capital (FC), urbanization (UP), renewable energy (RE), and energy intensity (EI), while explicitly accounting for how urbanization moderates the impacts of EC and FC through interaction terms.

Moving to the estimable econometric specification, we adopt a log-linear form for elasticity interpretation, with urbanization preserved in its original percentage scale due to its bounded nature (0–100%):

$$\ln EV_{it} = \beta_0 + \beta_1 \ln EC_{it} + \beta_2 \ln FC_{it} + \beta_3 UP_{it} + \beta_4 UP_{it}^2 + \beta_5 \ln RE_{it} + \beta_6 \ln EI_{it} + \beta_7 (\ln EC_{it} \times UP_{it}) + \beta_8 (\ln FC_{it} \times UP_{it}) + \epsilon_{it} \quad (9)$$

Here in Eq.9, the quadratic term for urbanization (UP^2) tests for potential nonlinear effects, such as the turning points predicted by ecological modernization theory. The interaction terms (EC×UP and FC×UP) operationalize the hypothesis that urbanization alters the environmental effects of economic production structures.

To quantify these conditional relationships, we derive the net (marginal) effects of EC and FC, which vary with urbanization levels:

$$\frac{\partial \ln EV_{it}}{\partial \ln EC_{it}} = \beta_1 + \beta_7 \cdot \ln UP_{it} \quad (10)$$

$$\frac{\partial \ln EV_{it}}{\partial \ln FC_{it}} = \beta_2 + \beta_8 \cdot \ln UP_{it} \quad (11)$$

These partial derivatives expressed in Eq.10 and Eq.11 will be evaluated at critical values of urbanization (minimum, mean, and maximum observed in the sample) to assess how urban contexts reshape EC's and FC's ecological impacts. For instance, a negative β_7 would imply that economic complexity's benefits for ecosystem vitality diminish in highly urbanized settings, while a positive β_8 could signal that urban agglomerations mitigate fixed capital's environmental costs.

Prior to formal estimation, we examine bivariate relationships between ecosystem vitality and core explanatory variables through graphical analysis plotted in Figure 1. These graphical representations provide an initial overview of how fundamental factors such as urbanization, economic complexity, energy intensity, and renewable energy may influence environmental performance.

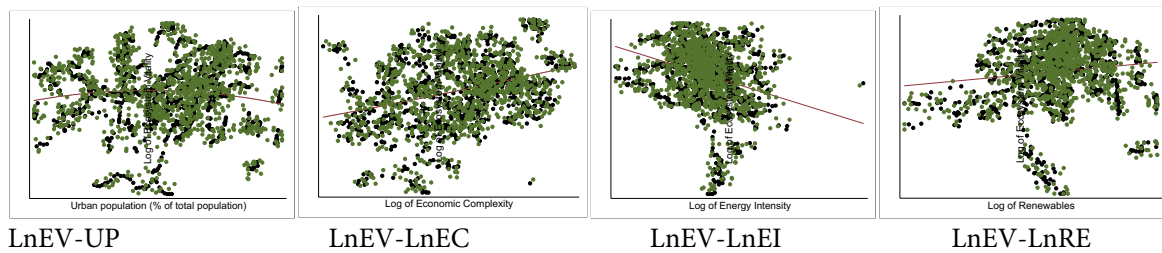


Figure 1. Observed relationships between ecosystem vitality and core explanatory variables.

Source: Own elaboration.

Figure 1(a) displays the bivariate association between urbanization and ecosystem vitality. The scatterplot reflects expected heterogeneity across OECD countries, and the curved fitted line indicates potential nonlinear effects. This visual evidence led us to formally test for quadratic urbanization effects in our econometric specifications. Figure 1(b) presents a positively sloped fitted line between economic complexity (LnEC) and ecosystem vitality. This visual pattern aligns with theoretical expectations that countries with more knowledge-intensive production structures may demonstrate superior environmental performance. The scatterplot in Figure 1(c) visualizes the association between energy intensity (LnEI) and ecosystem vitality. The downward-sloping fitted line preliminarily suggests that higher energy intensity may adversely affect environmental outcomes. Figure 1(d) illustrates the relationship between renewable energy use (LnRE) and ecosystem vitality. The upward-sloping fitted line provides initial evidence that renewable energy consumption may positively influence environmental outputs. The observed patterns in these figures undergo structural testing through formal empirical analyses in the later sections of our research

2.3 Methods

The methodology follows a systematic approach to address the unique challenges of panel data analysis while ensuring robust and reliable results. We begin with diagnostic tests to examine the fundamental properties of our dataset. Preliminary analyses confirm the presence of cross-sectional dependence and slope heterogeneity, rejecting the assumption of homogeneous parameters across countries. Unit root tests reveal mixed stationarity patterns, with some variables requiring first-differencing to achieve stationarity. These findings collectively justify our use of second-generation econometric techniques that explicitly account for these panel data complexities.

The model specification process involves formal testing of fixed versus random effects, with test results strongly favoring fixed effects estimation to control for unobserved country-specific heterogeneity. Additional diagnostic checks identify significant heteroskedasticity, autocorrelation, and cross-sectional dependence in the residuals, while supporting the exogeneity of our regressors. These diagnostic outcomes necessitate specialized estimation techniques that go beyond conventional panel data approaches.

For our core analysis, we implement multiple complementary estimation strategies to ensure robust inference. The primary approach employs panel-corrected standard errors (PCSE) developed by Beck and Katz (1995), to address heteroskedasticity and contemporaneous correlation. To simultaneously handle autocorrelation and cross-sectional dependence, we estimate models with Driscoll and Kraay (1998) standard errors incorporating first-order autoregressive correction (DK-AR1). Recognizing the bounded nature of our ecosystem vitality measures, we supplement these with Poisson pseudo-maximum likelihood estimation featuring high-dimensional fixed effects (PPML-HDFE), following Santos Silva and Tenreyro (2006), which provides consistent estimates under

various distributional assumptions. As a final robustness check, we implement feasible generalized least squares (FGLS) estimation to account for panel-specific heteroskedastic patterns (Parks, 1967).

This multi-method strategy serves two critical purposes. First, it allows us to assess whether our findings are robust to different statistical assumptions about error structures and functional forms. Second, it provides a wider framework to examine how urbanization moderates the environmental impacts of economic complexity and fixed capital formation. By systematically addressing the key challenges of panel data analysis - including cross-sectional dependence, heteroskedasticity, autocorrelation, and parameter heterogeneity - we ensure that our results reflect genuine relationships rather than statistical artifacts. In this respect, Figure 2 below depicts empirical methodology design.

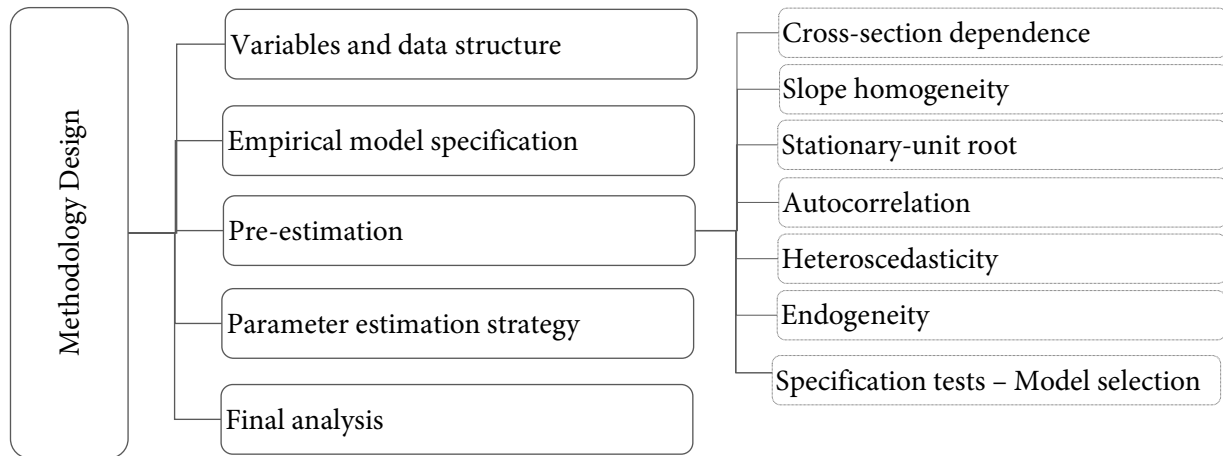


Figure 2. Methodology design.

Source: Own elaboration.

3. Research results

3.1 Descriptive Patterns and Correlations

Before proceeding to econometric analysis, it is critical to assess the distribution and variability of the dataset to ensure the robustness of subsequent estimations. Table 2 presents descriptive statistics for all variables, offering insights into the sample's empirical characteristics and potential outliers that may influence the results.

Table 2. Descriptive statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
EV	1064	50.679	9.727	21.69	70.761
EC	1064	1.646	0.653	0.01	3.047
FC	1064	2.438×10^{11}	5.622×10^{11}	1.443×10^9	4.675×10^{12}
UP	1064	76.178	11.105	50.622	98.153
RE	1064	165.813	327.821	0.016	2993.056
EI	1064	1.064	1.80×10^{-9}	1.05×10^{-9}	3.61×10^{-10}

Source: Own elaboration.

The statistics reveal several notable patterns. Ecosystem vitality (EV) exhibits a mean value of 50.68 (SD = 9.73), with a wide range (21.69–70.76), indicating significant cross-country and temporal heterogeneity in environmental performance across OECD nations. Economic complexity (EC) averages 1.65 (SD = 0.65), but its minimum (0.01) and maximum (3.05) values highlight disparities in productive sophistication, possibly reflecting divergent industrialization paths.

For gross fixed capital formation (FC), the substantial standard deviation (5.622×10^{11}) relative to the mean (2.438×10^{11}) suggests skewed investment distributions, likely due to economic size disparities (e.g., smaller vs. larger OECD economies). Urbanization (UP) is uniformly high (mean =

76.18%, SD = 11.11), consistent with OECD's urbanized demographics, though the range (50.62–98.15%) captures variations in urban concentration.

The energy variables show stark contrasts: Renewable energy (RE) has a high SD (327.82) and extreme max value (2,993.06), indicating outliers where certain countries rapidly scaled renewables. Energy intensity (EI)'s near-zero variability ($SD = 1.80 \times 10^{-9}$) suggests consistent measurement units.

Prior to estimating the multivariate regression model, we examine bivariate correlations between variables to identify potential multicollinearity issues and preliminary patterns in the data. Table 3 presents the correlation matrix for all key variables in the analysis.

Table 3. Matrix of correlations.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) EV	1.000					
(2) EC	0.324	1.000				
(3) FC	0.078	0.287	1.000			
(4) UP	-0.025	0.070	0.149	1.000		
(5) RE	0.012	0.155	0.826	0.150	1.000	
(6) EI	-0.243	-0.285	-0.113	-0.171	-0.044	1.000

Source: Own elaboration.

The correlation matrix reveals several important relationships. Ecosystem vitality (EV) shows a moderate positive correlation with economic complexity (EC) ($r = 0.324$), suggesting that countries with more sophisticated production structures tend to have better environmental performance. This aligns with ecological modernization theory, where advanced economies may develop technologies that reduce environmental impact. Notably, gross fixed capital formation (FC) demonstrates a strong positive correlation with renewable energy consumption (RE) ($r = 0.826$), indicating that higher investment levels are associated with greater renewable energy adoption. The negative correlation between energy intensity (EI) and EV ($r = -0.243$) supports the expected relationship where more energy-efficient economies tend to have higher ecosystem vitality. Similarly, EI's negative correlation with EC ($r = -0.285$) suggests that economically complex countries tend to use energy more efficiently. Urbanization (UP) shows weak correlations with most variables, with the strongest being a modest positive relationship with FC ($r = 0.149$). This implies that urban population share alone may not be a strong direct predictor of ecosystem vitality in OECD countries, supporting the inclusion of interaction terms to capture more nuanced relationships.

3.2 Model Diagnostics and Specification Tests

To ensure the reliability of our empirical analysis, we first examine the statistical properties of our dataset. Slope homogeneity was assessed based on the Delta and Swamy S tests proposed by Pesaran and Yamagata (2008), while cross-section independence was examined using CD, CDw, CDw+, and CD* statistics developed by Pesaran (2004, 2015) and Juodis and Reese (2022). Table 4 presents the results of cross-sectional dependence and slope homogeneity tests for OECD countries. The Pesaran (2015)-type CD test (statistic = 9.66, $p < 0.01$) and its power-enhanced version CDw+ (statistic = 1739.20, $p < 0.01$) reveal strong cross-sectional dependence in our panel. This finding suggests the presence of either mutual interactions in environmental policies among countries or their simultaneous exposure to common global shocks. Regarding slope homogeneity, both the Swamy S test ($\chi^2 = 17563.11$, $p < 0.01$) and Delta test ($\Delta = 28.124$, $p < 0.01$) indicate statistically significant parameter heterogeneity across countries.

Table 4. Slope homogeneity and cross-section independence tests.

CD Tests				Homogeneity	
CD	CDw	CDw+	CD*	Delta	Swamy S (χ^2)
9.66*	-1.67***	1739.20*	-0.43	28.124*	17563.11*

Note: * $p < 0.01$, ** $p < 0.05$, *** $p < 0.10$.

Source: Own elaboration.

These results demonstrate that conventional fixed or random effects models might produce misleading inferences. Cross-sectional dependence may substantially underestimate standard errors, creating false significance risks, while unaccounted slope heterogeneity could mask country-specific dynamics crucial for policy recommendations. Therefore, building on these findings, the empirical strategy proceeds by selecting the most appropriate advanced panel methods based on the unit root tests (Table 5) and model selection criteria (Table 6). When the tests show consistent patterns, the analysis prioritizes estimators that simultaneously correct for cross-sectional dependence and accommodate heterogeneous coefficients.

The CDw test results (statistic = -1.67, $p < 0.10$), validated by Juodis and Reese's (2022) simulation studies, provide additional albeit weaker evidence of dependence. These findings align with the hypothesis that coordinated environmental regulations (e.g., Paris Agreement) among OECD nations may strengthen cross-sectional linkages. Our final model selection in Table 8 will explicitly address these statistical properties while maintaining theoretical relevance to ecological institutionalism.

Table 5 presents the results of the panel unit root tests, which explore the time-series characteristics of the variables while accounting for cross-sectional dependence. Following Pesaran (2007), the CADF and CIPS tests were applied to accommodate potential cross-sectional correlations among OECD countries. These results offer a foundation for identifying the stationarity properties of the variables and guiding the appropriate model specification.

Table 5. Pesaran-CIPS and CADF panel unit root test.

Variable	CIPS I(0)	CIPS I(1)	CADF I(0)	CADF I(1)
EV	-2.274	-4.776*	-2.274	-4.776*
EC	-2.557	-4.666*	-2.457	-3.076*
FC	-2.021	-4.163*	-2.389	-3.30*
UP	-1.185	-2.363*	-1.671	-2.147*
RE	-2.854*	.	-2.873**	.
EI	-2.296	-4.901*	-2.063	-3.708*
I_EC	-2.547	-4.671*	-2.448	-3.088*
I_FC	-1.787	-4.093*	-2.134	-3.278*

Note: * $p < 0.01$, ** $p < 0.05$.

Source: Own elaboration.

The unit root test results in Table 5 demonstrate that renewable energy (RE) is the only variable exhibiting stationarity in levels, with both CIPS (-2.854, $p < 0.01$) and CADF (-2.873**, $p < 0.05$) tests rejecting the unit root hypothesis. All other variables - including ecosystem vitality (EV), economic complexity (EC), fixed capital (FC), urbanization (UP), energy intensity (EI), and both interaction terms (I_EC and I_FC) - show consistent patterns of non-stationarity at levels but achieve stationarity after first differencing, as evidenced by statistically significant results ($p < 0.01$) across both test frameworks. These findings indicate that while RE can be analyzed in its level form, the other variables will require appropriate differencing transformations to ensure valid statistical inference in subsequent modeling. The consistent results across both testing approaches lend robustness to these stationarity assessments and provide clear guidance for variable treatment in our empirical analysis.

Before proceeding to estimation, it is essential to determine the appropriate panel data specification that accounts for unobserved heterogeneity. Table 6 presents the results of diagnostic tests for individual and time effects, along with the Hausman test, which collectively guide the choice between fixed, random, or pooled effects models.

Table 6. Specification tests for panel effects and model selection.

	Individual Effect	Time Effect	Mix Effet
LR	$\chi^2=919.47^*$	$\chi^2=18.85^*$	$\chi^2=1741.94^*$
F	F test=122.30*	F test= 13.51*	
LM	$\chi^2= 7811.50^*$		
Hausman Test	$\chi^2 = 53.72^*$		

Note: * $p < 0.01$.

Source: Own elaboration.

The specification test results in Table 6 provide crucial evidence for determining the appropriate panel data model structure. The highly significant likelihood ratio (LR) statistics for individual effects ($\chi^2=919.47$, $p=0.000$), time effects ($\chi^2=18.85$, $p=0.000$), and mixed effects ($\chi^2=1741.94$, $p=0.000$) collectively reject the null hypothesis of no unobserved heterogeneity, indicating that both country-specific and time-specific factors significantly influence our dependent variable. This conclusion is further supported by the F-test results, which similarly confirm the presence of individual effects ($F=122.30$, $p=0.000$) and time effects ($F=13.51$, $p=0.000$). The remarkably large Lagrange Multiplier (LM) statistic ($\chi^2=7811.50$, $p=0.000$) provides additional strong evidence favoring panel data approaches over pooled OLS estimation. Most critically, the Hausman test yields a statistically significant result ($\chi^2=53.72$, $p=0.000$), decisively rejecting the random effects model in favor of fixed effects specification. These comprehensive test results collectively demonstrate that our empirical analysis requires a fixed effects modeling framework that accounts for both individual country heterogeneity and time-specific variations to produce unbiased and efficient parameter estimates. The overwhelming statistical evidence across all test categories leaves little doubt about the necessity of controlling for unobserved individual and time effects in our panel data analysis.

Before presenting the estimation results, we examine whether our empirical models satisfy key statistical assumptions. Table 7 reports diagnostic tests for heteroskedasticity, autocorrelation, cross-sectional dependence, and endogeneity—potential violations that could bias estimates if unaddressed. These tests validate the robustness of our chosen specifications.

Table 7. Diagnostic tests for model assumptions.

Tests	Hypothesis	Statistics	p-value
Breusch-Pagan / Cook-Weisberg	$H_0: \text{Var}(u_i) = \sigma^2$	$\chi^2 = 63$	0.000
White's test	$H_0: \text{Var}(u_i) = \sigma^2$	$\chi^2 = 377$	0.000
Wooldridge test	$H_0: \text{Cov}(u_{it}, u_{is}) = 0 \forall t \neq s$	$F = 371$	0.000
Breusch-Pagan LM	$H_0: \text{Cov}(u_{it}, u_{jt}) = 0 \forall i \neq j$	$\chi^2 = 5792$	0.000
Durbin (score)	$H_0: \text{Cov}(X_{it}, u_{it}) = 0$	$\chi^2 = 1.93$	0.165
Wu-Hausman	$H_0: \text{Cov}(X_{it}, u_{it}) = 0$	$F = 1.922$	0.166

Source: Own elaboration.

The diagnostic tests in Table 7 reveal several critical insights about our model's properties. First, both the Breusch-Pagan ($\chi^2=63$, $p=0.000$) and White's tests ($\chi^2=377$, $p=0.000$) strongly reject the null hypothesis of homoskedasticity, indicating significant heteroskedasticity that necessitates robust standard errors in estimation. Second, the Wooldridge test ($F=371$, $p=0.000$) confirms the presence of first-order autocorrelation, further supporting the use of panel-corrected techniques.

The Breusch-Pagan LM test ($\chi^2=5792$, $p=0.000$) overwhelmingly rejects cross-sectional independence, aligning with our earlier findings of interconnectedness among OECD countries. Crucially, the Durbin ($\chi^2=1.93$, $p=0.165$) and Wu-Hausman ($F=1.922$, $p=0.166$) tests fail to reject the null of exogeneity, suggesting our regressors can be treated as exogenous, a finding that justifies the chosen estimators while precluding the need for instrumental variables.

3.3 Estimation Results

Following the diagnostic results, several methodological adjustments were necessary to ensure the robustness of our empirical approach. To address heteroskedasticity and serial correlation simultaneously, we relied on Driscoll-Kraay standard errors with first-order autoregressive correction (Driscoll & Kraay, 1998). In addition, Panel-Corrected Standard Errors (PCSE) estimation was applied to control for contemporaneous correlation and heteroskedasticity across panels (Beck & Katz, 1995). Feasible Generalized Least Squares (FGLS) estimation was also employed to address panel-specific heteroskedastic patterns and serial correlation, drawing on both classical and contemporary implementations (Parks, 1967; Greene, 2003). Finally, to handle cross-sectional dependence and the semi-continuous nature of the dependent variable, Poisson Pseudo Maximum Likelihood with high-dimensional fixed effects (PPML-HDFE) was implemented (Santos Silva &

Tenreyro, 2006; Correia, Guimarães, & Zylkin, 2020). These methodological adaptations collectively ensure that our empirical strategy remains resilient to the identified violations of classical regression assumptions. The estimation outcomes based on these adjustments are reported in Table 8.

Table 8. Estimations.

Variable	PCSE	DK-AR1	PPML-HDFE	FGLS
LnEC	0.58** (2.52)	0.80* (3.58)	0.78* (8.74)	0.62* (7.68)
LnFC	-0.67* (-2.6)	-0.95* (-4.02)	-0.51* (-13.09)	-0.70* (-14.04)
UP	-0.095* (-2.63)	-0.137* (-4.19)	-0.064* (-12.04)	-0.098* (11.52)
UPS	0.0003** (2.41)	0.0004* (3.98)	0.0002* (9.92)	0.0003* (7.99)
LnRE	0.0270* (3.4)	0.0266* (3.59)	0.0040* (4.73)	0.0232* (16.84)
LnEI	-0.035* (-3.18)	-0.046* (-3.94)	-0.035* (-9.93)	-0.027* (9.66)
I_EC	-0.129** (-2.44)	-0.177* (-3.48)	-0.172* (-8.42)	-0.139* (7.57)
I_FC	0.157* (2.65)	0.221* (4.06)	0.116* (13.08)	0.162* (13.9)
cons	8.21* (3.89)	10.62* (5.43)	4.71* (15.66)	8.77* (20.58)

Note: * $p < 0.01$, ** $p < 0.05$, (z-statistics).

Source: Own elaboration.

The estimation results presented in Table 8 demonstrate remarkable consistency across four distinct methodologies, reinforcing the robustness of our findings. Beginning with economic complexity (LnEC), all models show statistically significant positive effects, with coefficients ranging from 0.58 (PCSE) to 0.80 (DK-AR1), suggesting that advanced economic structures consistently contribute to improved environmental outcomes. The negative coefficients for fixed capital formation (LnFC), ranging from -0.51 (PPML-HDFE) to -0.95 (DK-AR1), indicate that traditional investment patterns may exert persistent environmental pressures across OECD nations.

Urbanization (UP) displays uniformly negative and significant coefficients (-0.064 to -0.137), supporting the hypothesis that urban expansion initially strains ecosystems, while its squared term (UPS) reveals a consistent positive turning point (0.0002 to 0.0004), corroborating the Environmental Kuznets Curve hypothesis for urbanization effects. Renewable energy (LnRE) maintains positive significance across all specifications (0.0040 to 0.0270), though the magnitude varies considerably, with FGLS showing the strongest effect (0.0232) and PPML-HDFE the most conservative (0.0040).

Energy intensity (LnEI) exhibits expected negative coefficients (-0.027 to -0.046), confirming that energy efficiency improvements consistently benefit ecosystem vitality. The interaction terms reveal nuanced insights: I_EC 's negative coefficients (-0.129 to -0.177) suggest that economic complexity's environmental benefits diminish in highly urbanized contexts, while I_FC 's positive coefficients (0.116 to 0.221) imply urbanization mitigates fixed capital's negative environmental impacts.

Notably, the PPML-HDFE estimates generally show larger absolute z-statistics, reflecting the method's efficiency in handling our data's characteristics. The consistency of significance levels ($p < 0.01$, $p < 0.05$) across methods, despite their different handling of heteroskedasticity, autocorrelation, and cross-sectional dependence, strongly validates our core findings. The constant terms' variation (4.71 to 10.62) appropriately captures method-specific baseline differences while maintaining the relative stability of other coefficients.

This analysis confirms that our key results are not artifacts of specific methodological choices, but represent robust relationships observable across diverse estimation frameworks. The convergence of findings from PCSE (addressing heteroskedasticity), DK-AR1 (handling autocorrelation), PPML-HDFE (managing cross-sectional dependence), and FGLS (optimizing efficiency) provides particularly strong evidence for our hypothesized relationships. The minor variations in coefficient magnitudes offer valuable insights into how different data challenges affect parameter estimation, with all methods ultimately supporting the same substantive conclusions about the urbanization-environment nexus in OECD countries.

3.4 Interaction Terms and Urban Moderation

To fully capture how urbanization moderates the environmental impacts of economic complexity and fixed capital, Table 9 presents the net (marginal) effects calculated across minimum, mean, and maximum urban population levels. These results, derived from four robust estimation methods, reveal the conditional nature of the relationships identified in our main specifications, offering nuanced policy insights.

Table 9. Net effects of economic complexity and fixed capital on ecosystem vitality across urbanization levels.

Net effect	PCSE	DK-AR1	PPML-HDFE	FGLS
LnEC @ UPmin (0.506)	0.51	0.71	0.69	0.55
LnEC @ UPmean (0.762)	0.48	0.67	0.65	0.51
LnEC @ UPmax (0.982)	0.45	0.63	0.61	0.48
LnFC @ UPmin (0.506)	-0.59	-0.84	-0.45	-0.62
LnFC @ UPmean (0.762)	-0.55	-0.78	-0.42	-0.58
LnFC @ UPmax (0.982)	-0.52	-0.73	-0.40	-0.54

Notes: UP (urban population) scaled to 0-1 range. Net effects for LnEC calculated as $\beta_1 + \beta_7 \cdot \text{LnUP}_{it}$, for LnFC as $\beta_2 + \beta_8 \cdot \text{LnUP}_{it}$, and evaluated at $\text{UP} \in \{\text{UP}_{\min}, \text{UP}_{\text{mean}}, \text{UP}_{\max}\}$ to assess urban moderation effects.

Source: Own elaboration.

The net effects presented in Table 9 reveal patterns about how urbanization moderates the environmental impacts of economic complexity and fixed capital. For economic complexity (LnEC), we observe a consistent but diminishing positive effect across urbanization levels. The PCSE estimates, for instance, show that a one-unit increase in LnEC improves ecosystem vitality by 0.51 units at minimum urbanization ($\text{UP}=0.506$), declining to 0.48 units at mean urbanization ($\text{UP}=0.762$), and further to 0.45 units at maximum urbanization ($\text{UP}=0.982$). This gradual attenuation suggests that while knowledge-intensive production structures benefit ecosystems, their marginal utility weakens in highly urbanized contexts, possibly due to saturation of technological spillovers or intensified resource competition in dense urban areas. A similar pattern emerges across all four estimation methods, with the DK-AR1 model showing slightly stronger effects and PPML-HDFE yielding more conservative estimates, reflecting methodological differences in handling panel data challenges.

For fixed capital (LnFC), the net negative effects persist but exhibit meaningful moderation with urbanization. The DK-AR1 results illustrate this trend most clearly: at minimum urbanization, a one-unit increase in LnFC reduces ecosystem vitality by 0.84 units, while at maximum urbanization, this penalty softens to 0.73 units. This pattern implies that urban environments may partially counteract the ecological costs of physical capital accumulation through agglomeration benefits, more efficient infrastructure utilization, or stricter urban environmental regulations. The consistency of this moderating effect across PCSE, FGLS, and PPML-HDFE specifications - despite their distinct approaches to addressing heteroskedasticity and dependence - strengthens confidence in this finding.

The comparative stability of these net effects across estimation methods is particularly noteworthy. While coefficient magnitudes vary predictably (with PPML-HDFE typically producing smaller absolute values due to its exponential mean specification), all models agree on both the direction of effects and their urbanization-contingent nature. This robustness underscores that our core findings about urban moderation are not artifacts of specific methodological choices, but reflect fundamental relationships in the data. The results collectively suggest that urban planners and policymakers should consider place-specific strategies: promoting economic complexity may yield greater environmental dividends in less urbanized regions, whereas mitigating fixed capital's ecological impact could prove most effective in highly urbanized areas through targeted investments in green infrastructure and circular economy practices.

3.5 Marginal Effects Visualization

To further explore the role of urbanization in conditioning the environmental effects of structural economic variables, we present marginal effect plots in Figure 3. These visualizations illustrate how the impact of economic complexity (LnEC) and fixed capital formation (LnFC) on ecosystem vitality (EV) varies across different levels of urban population.

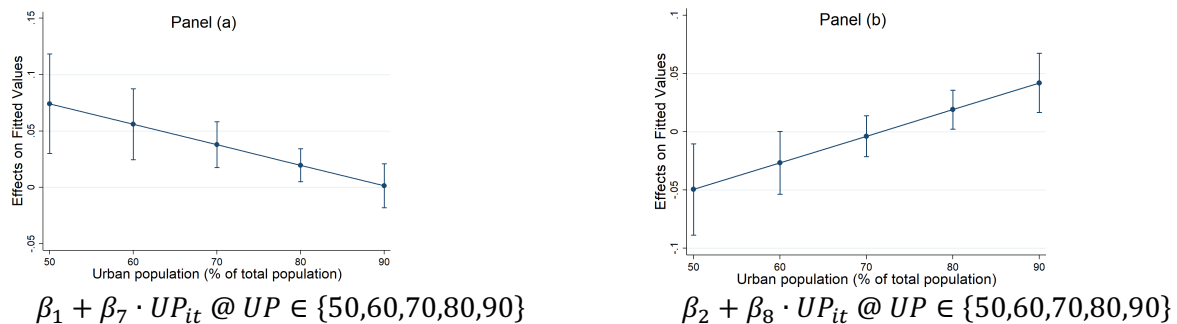


Figure 3. Urbanization as a Moderator of the Effects of Economic Complexity and Fixed Capital on Ecosystem Vitality.

Source: Own elaboration.

Fig. 3(a) reveals that the marginal effect of economic complexity declines steadily as urbanization increases. At lower urban population levels (e.g., 50%), economic complexity yields a significantly positive contribution to ecosystem vitality. However, as the urban population approaches 90%, this effect becomes statistically indistinct. These results are consistent with the net effect estimates reported in Table 9, which show a gradual attenuation of ECI's environmental benefits across increasing urbanization levels. This finding supports the hypothesis that while knowledge-intensive production structures promote environmental improvements, their marginal utility may decline in densely urbanized contexts due to resource saturation, congestion, or diminishing technological returns.

Fig. 3(b), in contrast, demonstrates a reverse moderation pattern. The marginal effect of fixed capital formation increases with urbanization, turning from negative at lower urbanization rates to positive and statistically significant at higher levels. This suggests that urban environments enhance the environmental efficiency of capital investments—possibly due to better infrastructure integration, agglomeration effects, and stronger environmental regulations in densely populated regions. Again, the graphical insights align closely with the coefficient trends in Table 9, where the environmental cost of fixed capital decreases across urbanization tiers.

Fig. 3 corroborates our main hypothesis that urbanization not only exerts a direct influence on environmental quality but also reshapes the environmental implications of key structural drivers. The consistency of these patterns across four estimation techniques, PCSE, DK-AR1, PPML-HDFE, and FGLS, confirms the robustness of our findings and underscores the significance of spatial context in environmental-economic modeling.

4. Discussion

The findings of this study yield several critical insights into the environmental implications of economic structure and urbanization. First, the diminishing marginal benefits of economic complexity in highly urbanized contexts resonate with the saturation hypothesis advanced by Fritz and Manduca (2021), who argue that knowledge spillovers and innovation gains may plateau once urban systems reach a certain density threshold. This observation reinforces the idea that technological sophistication alone is insufficient to generate sustained ecological improvements without concurrent institutional and spatial transformations.

Second, the moderating role of urbanization in attenuating the environmental costs of capital formation aligns with evidence from Chang et al. (2024), which underscores how agglomeration

economies in urban environments can enhance the efficiency of infrastructure deployment and resource allocation. This suggests that well-planned urban growth may buffer the traditionally negative ecological effects of capital accumulation.

Furthermore, the identification of an inverted-U relationship between urbanization and environmental performance provides empirical support for the Urban Environmental Kuznets Curve (UEKC) hypothesis (Cheng et al., 2023). This pattern implies that environmental degradation may initially rise with urban expansion but improve once cities surpass critical thresholds in regulatory capacity, institutional quality, and clean technologies.

Collectively, these findings substantiate core tenets of Ecological Modernization Theory (Mol & Spaargaren, 2000), especially the notion that structural reform and innovation, when embedded in spatially adaptive frameworks, can yield ecological dividends. Importantly, this study extends prior research by modeling urbanization not merely as an independent driver but as a moderating structure that shapes the effects of economic inputs on ecosystem vitality.

From a policy standpoint, the results advocate for a more nuanced approach to sustainability in high-income contexts. Policymakers should focus not only on promoting technological advancement and capital investment but also on strengthening urban institutions, enhancing spatial planning, and fostering region-specific environmental governance models that integrate urban density, complexity-driven innovation, and infrastructural efficiency.

Conclusions

This study, based on panel data from 38 OECD countries over the period 1995–2022, demonstrates that urbanization significantly moderates how economic complexity and capital formation influence environmental outcomes. Rather than serving as a passive backdrop, urban contexts actively condition both the direction and magnitude of these structural impacts on ecosystem vitality.

Three key findings emerge. First, the positive environmental contributions of economic complexity weaken as urban density increases. This attenuation likely reflects challenges such as congestion, resource competition, and diminishing returns to innovation in highly urbanized settings. Second, urbanization appears to mitigate the ecological costs associated with capital accumulation, likely through more efficient infrastructure use, shared systems, and stronger regulatory oversight. Third, the analysis confirms a nonlinear (inverted U-shaped) relationship between urbanization and environmental performance, consistent with the Urban Environmental Kuznets Curve hypothesis. Environmental degradation initially intensifies during early stages of urban growth but tends to improve once cities reach more advanced levels of development, likely due to enhanced governance capacities and greater diffusion of green technologies. This finding underscores the importance of urban governance capacity and integrated planning in achieving environmental sustainability, as emphasized by global frameworks (UN-Habitat, 2022).

The findings concerning energy dynamics reveal additional nuances. While renewable energy adoption consistently improves environmental quality, persistently high energy intensity continues to pose significant challenges. This suggests that while transitioning to renewable energy is essential, complementary strategies, such as implementing energy efficiency standards and promoting circular economy practices, are also critical for reducing overall energy demand and achieving deeper environmental gains.

From a policy perspective, these insights underscore the importance of spatially differentiated approaches. Efforts to promote economic complexity could be more effective when tailored to peri-urban or moderately dense areas, whereas capital investment strategies may benefit from focusing on compact, resource-efficient urban forms. Rather than viewing urbanization as uniformly beneficial or detrimental, policymakers are encouraged to recognize its contingent effects and design sustainability strategies that are sensitive to local urban contexts.

Theoretically, this study contributes to the ecological modernization literature by reframing urbanization as a moderating mechanism rather than an independent driver of environmental

change. It also reinforces the Urban Environmental Kuznets Curve (UEKC) hypothesis by showing that sustainability outcomes hinge not only on affluence, but also on institutional maturity and technological absorption. Practically, the findings highlight the need for differentiated sustainability strategies that align with urban form, economic complexity, and capital dynamics.

Nonetheless, several limitations should be acknowledged. First, this study relies on country-level panel data, which may obscure important intra-national differences in urban structure and environmental governance. Second, while the analysis incorporates key structural and energy-related variables, it does not account for potentially influential institutional or cultural factors. Third, the exclusive focus on OECD countries may limit the generalizability of the findings to non-OECD or developing contexts.

Future research could further explore whether these moderating dynamics vary across (1) different regional groupings, (2) stages of economic development, or (3) urban governance models. Additionally, city-level analyses could offer more granular insights into how intra-urban variations shape the links between economic structure, urbanization, and environmental outcomes. City-level evidence further supports the dynamic relationship between urban growth and air quality (Zhu, 2025), highlighting the relevance of localized analyses in urban environmental studies. By conceptualizing urbanization as an active moderating force, this study offers a more sophisticated interpretation of how economic and ecological systems interact during sustainability transitions.

Funding: The author received no financial support for the research, authorship, and/or publication of this article.

Data Availability Statement: The data that support the findings of this study are available from the author upon reasonable request.

Conflicts of Interest: The author declares that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Reference

1. Adebayo, T. S., & Kirikkaleli, D. (2022). Capital formation, green innovation, renewable energy consumption, and CO₂ emissions in G7 countries: A quantile regression approach. *Environmental Science and Pollution Research*, 29, 12345–12360. <https://doi.org/10.1007/s11356-021-16913-6>.
2. Aluko, O., Opoku, E., & Acheampong, A. (2023). Economic complexity and environmental degradation: Evidence from OECD countries. *Business Strategy and the Environment*, 32(6), 2767–2788. <https://doi.org/10.1002/bse.3269>.
3. Balland, P., Jara-Figueroa, C., Petralia, S., Steijn, M., Rigby, D., & Hidalgo, C. (2020). Complex economic activities concentrate in large cities. *Nature Human Behaviour*, 4, 248–254. <https://doi.org/10.1038/s41562-019-0803-3>.
4. Balsalobre-Lorente, D., Shahbaz, M., Murshed, M., & Nuță, F. (2023). Environmental impact of globalization: The case of central and Eastern European emerging economies. *Journal of Environmental Management*, 341, Article 118018. <https://doi.org/10.1016/j.jenvman.2023.118018>.
5. Bashir, M. F., Ma, B., Hussain, H. I., Shahbaz, M., Koca, K., & Shahzadi, I. (2022). Evaluating environmental commitments to COP21 and the role of economic complexity, renewable energy, financial development, urbanization, and energy innovation: Empirical evidence from the RCEP countries. *Renewable Energy*, 184, 541–550. <https://doi.org/10.1016/j.renene.2021.11.102>.
6. Beck, N., & Katz, J. N. (1995). What to do (and not to do) with time-series cross-section data. *American Political Science Review*, 89(3), 634–647. <https://doi.org/10.2307/2082979>.
7. Boleti, E., Garas, A., Kyriakou, A., & Lapatinas, A. (2021). Economic complexity and environmental performance: Evidence from a world sample. *Environmental Modeling & Assessment*, 26, 251–270. <https://doi.org/10.1007/s10666-021-09750-0>.

8. Burger, J. R., Brown, J. H., Day, J. W., Flanagan, T. P., & Roy, E. D. (2019). The central role of energy in the urban transition: Global challenges for sustainability. *Biophysical Economics and Resource Quality*, 4(1), Article 5. <https://doi.org/10.1007/s41247-019-0053-z>.
9. Cao, N., Ling, S., & Cui, X. (2025). Measurement and comparative analysis of Chinese new-type urbanization and eco-environment system coordination. *Sustainability*, 17(5), Article 1824. <https://doi.org/10.3390/su17051824>.
10. Chang, G., Yasin, I., & Naqvi, S. M. M. A. (2024). Environmental sustainability in OECD nations: The moderating impact of green innovation on urbanization and green growth. *Sustainability*, 16(16), Article 7047. <https://doi.org/10.3390/su16167047>.
11. Cheng, Y., Chen, X., Sun, H., & Zhu, H. (2023). Spatio-temporal heterogeneity and driving mechanisms of urbanization impact on ecosystem service values in the Yellow River Basin, China. *Land*, 12(7), Article 1301. <https://doi.org/10.3390/land12071301>.
12. Churkina, G. (2016). The role of urbanization in the global carbon cycle. *Frontiers in Ecology and Evolution*, 3, Article 144. <https://doi.org/10.3389/fevo.2015.00144>.
13. Correia, S., Guimarães, P., & Zylkin, T. (2020). Fast Poisson estimation with high-dimensional fixed effects. *The Stata Journal*, 20(1), 95–115. <https://doi.org/10.1177/1536867X20909691>.
14. Das, R. C., Chatterjee, T., & Ivaldi, E. (2021). Sustainability of urbanization, non-agricultural output and air pollution in the world's top 20 polluting countries. *Data*, 6(6), Article 65. <https://doi.org/10.3390/data6060065>.
15. Degirmenci, T., Sofuoglu, E., & Aydin, M. (2024). The role of energy intensity, green energy transition, and environmental policy stringency on environmental sustainability in G7 countries. *Clean Technologies and Environmental Policy*, 26(8), 1–13. <https://doi.org/10.1007/s10098-024-02968-y>.
16. Di Clemente, R., Strano, E., & Batty, M. (2021). Urbanization and economic complexity. *Scientific Reports*, 11, Article 6667. <https://doi.org/10.1038/s41598-021-83238-5>.
17. Doğan, B., Saboori, B., & Can, M. (2019). Does economic complexity matter for environmental degradation? An empirical analysis for different stages of development. *Environmental Science and Pollution Research*, 26, 31900–31912. <https://doi.org/10.1007/s11356-019-06333-1>.
18. Driscoll, J. C., & Kraay, A. C. (1998). Consistent covariance matrix estimation with spatially dependent panel data. *The Review of Economics and Statistics*, 80(4), 549–550. <https://doi.org/10.1162/003465398557825>.
19. Duranton, G., & Puga, D. (2004). Micro-foundations of urban agglomeration economies. In J. V. Henderson & J.-F. Thisse (Eds.), *Handbook of regional and urban economics: Cities and geography* (Vol. 4, pp. 2063–2117). Elsevier. [https://doi.org/10.1016/S1574-0080\(04\)80005-1](https://doi.org/10.1016/S1574-0080(04)80005-1).
20. Franco, S., Mandla, V. R., & Rao, K. R. M. (2017). Urbanization, energy consumption and emissions in the Indian context: A review. *Renewable and Sustainable Energy Reviews*, 74, 836–846. <https://doi.org/10.1016/j.rser.2016.12.117>.
21. Fritz, B., & Manduca, R. (2021). The economic complexity of US metropolitan areas. *Regional Studies*, 55(8), 1299–1310. <https://doi.org/10.1080/00343404.2021.1884215>.
22. Gomez-Lievano, A., & Patterson-Lomba, O. (2021). Estimating the drivers of urban economic complexity and their connection to economic performance. *Royal Society Open Science*, 8, 210670. <https://doi.org/10.1098/rsos.210670>.
23. Greene, W. H. (2003). *Econometric analysis* (5th ed.). Prentice Hall.
24. Harvard Growth Lab. (2024). *The Atlas of Economic Complexity*. <https://atlas.hks.harvard.edu/rankings>.
25. Hassan, S., Wang, P., Khan, I., & Zhu, B. (2023). The impact of economic complexity, technology advancements, and nuclear energy consumption on the ecological footprint of the USA: Towards circular economy initiatives. *Gondwana Research*, 113, 237–246. <https://doi.org/10.1016/j.gr.2022.11.001>.

26. Hidalgo, C. A., & Hausmann, R. (2009). The building blocks of economic complexity. *Proceedings of the National Academy of Sciences*, 106(26), 10570–10575. <https://doi.org/10.1073/pnas.0900943106>.
27. International Energy Agency. (2024). *Statistical Review of World Energy – SDG7 Database*. <https://www.iea.org/data-and-statistics/data-product/sdg7-database>.
28. Juodis, A., & Reese, S. (2022). The incidental parameters problem in testing for remaining cross-section correlation. *Journal of Business & Economic Statistics*, 40(3), 1191–1203. <https://doi.org/10.1080/07350015.2021.1906687>.
29. Khezri, M., Heshmati, A., & Khodaei, M. (2022). Environmental implications of economic complexity and its role in determining how renewable energies affect CO₂ emissions. *Applied Energy*, 306, Article 117948. <https://doi.org/10.1016/j.apenergy.2021.117948>.
30. Kusiya, K., Mushtaq, M., Ahmed, S., Abbas, A., & Fahlevi, M. (2024). Impact of urbanization on environmental eminence: Moderating role of renewable energy. *International Journal of Energy Economics and Policy*, 14(2), 244–257. <https://doi.org/10.32479/ijeep.14232>.
31. Kwilinski, A., Lyulyov, O., & Pimonenko, T. (2023). The effects of urbanisation on green growth within sustainable development goals. *Land*, 12(2), Article 511. <https://doi.org/10.3390/land12020511>.
32. Lapatinas, A., Litina, A., & Poullos, K. (2022). Economic complexity of cities and its role for resilience. *PLOS ONE*, 17(7), Article e0269797. <https://doi.org/10.1371/journal.pone.0269797>.
33. Latief, R., Sattar, U., Javeed, S. A., Gull, A. A., & Pei, Y. (2022). The environmental effects of urbanization, education, and green innovation in the Union for Mediterranean countries: Evidence from quantile regression model. *Energies*, 15(15), Article 5456. <https://doi.org/10.3390/en15155456>.
34. Liang, Y., Ur Rahman, S., Shafaqat, A., Ali, A., Ali, M. S. E., & Khan, H. (2024). Assessing sustainable development in E-7 countries: Technology innovation, and energy consumption drivers of green growth and environment. *Scientific Reports*, 14, Article 79908. <https://doi.org/10.1038/s41598-024-79908-9>.
35. Liu, S., Yang, M., Mou, Y., Meng, Y., Zhou, X., & Peng, C. (2020). Effect of urbanization on ecosystem service values in the Beijing-Tianjin-Hebei urban agglomeration of China from 2000 to 2014. *Sustainability*, 12(24), Article 10233. <https://doi.org/10.3390/su122410233>.
36. Mankiw, N. G., Romer, D., & Weil, D. N. (1992). A contribution to the empirics of economic growth. *The Quarterly Journal of Economics*, 107(2), 407–437. <https://doi.org/10.2307/2118477>.
37. McGranahan, G., Balk, D., & Anderson, B. (2007). The rising tide: assessing the risks of climate change and human settlements in low elevation coastal zones. *Environment and Urbanization*, 19(1), 17–37. <https://doi.org/10.1177/0956247807076960>.
38. Mealy, P., & Teytelboym, A. (2022). Economic complexity and the green economy. *Research Policy*, 51(8), 103948. <https://doi.org/10.1016/j.respol.2020.103948>.
39. Mol, A. P. J., & Spaargaren, G. (2000). Ecological modernization theory in debate: A review. *Environmental Politics*, 9(1), 17–49. <https://doi.org/10.1080/09644010008414511>.
40. OECD. (2023). *Sustainable urban development*. OECD Publishing. Retrieved from <https://www.oecd.org/en/topics/sustainable-urban-development.html>.
41. Onifade, S. T., & Alola, A. A. (2023). Environmental quality outlook of the leading oil producers and urbanized African states. *Environmental Science and Pollution Research*, 30(45), 67523–67538. <https://doi.org/10.1007/s11356-023-28915-w>.
42. Parks, R. W. (1967). *Efficient estimation of a system of regression equations when disturbances are both serially and contemporaneously correlated*. *Journal of the American Statistical Association*, 62(318), 500–509. <https://doi.org/10.2307/2283977>.
43. Pata, U. (2021). Renewable and non-renewable energy consumption, economic complexity, CO₂ emissions, and ecological footprint in the USA: Testing the EKC hypothesis with a structural

- break. *Environmental Science and Pollution Research*, 28, 846–861. <https://doi.org/10.1007/s11356-020-10446-3>.
44. Pesaran, M. H. (2004). General diagnostic tests for cross section dependence in panels. *Cambridge Working Papers. Economics*, 1240(1), Article 1. <https://doi.org/10.2139/ssrn.572504>.
 45. Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics*, 22(2), 265–312. <https://doi.org/10.1002/jae.951>.
 46. Pesaran, M. H. (2015). Testing weak cross-sectional dependence in large panels. *Econometric Reviews*, 34(6–10), 1089–1117. <https://doi.org/10.1080/07474938.2014.956623>.
 47. Pesaran, M. H., & Yamagata, T. (2008). Testing slope homogeneity in large panels. *Journal of Econometrics*, 142(1), 50–93. <https://doi.org/10.1016/j.jeconom.2007.05.010>.
 48. Prakash, N., & Sethi, M. (2023). Relationship between fixed capital formation and carbon emissions: Impact of trade liberalization in India. *Cogent Economics & Finance*, 11(1), Article 2245274. <https://doi.org/10.1080/23322039.2023.2245274>.
 49. Radoine, H., Bajja, S., Chenal, J., & Ahmed, Z. (2022). Impact of urbanization and economic growth on environmental quality in Western Africa: Do manufacturing activities and renewable energy matter? *Frontiers in Environmental Science*, 10, Article 1012007. <https://doi.org/10.3389/fenvs.2022.1012007>.
 50. Romero, J., & Gramkow, C. (2021). Economic complexity and greenhouse gas emissions. *World Development*, 139, Article 105317. <https://doi.org/10.1016/j.worlddev.2020.105317>.
 51. Salvati, L., & Carlucci, M. (2020). Shaping dimensions of urban complexity: The role of economic structure and socio-demographic local contexts. *Social Indicators Research*, 147, 263–285. <https://doi.org/10.1007/s11205-019-02156-2>.
 52. Santos Silva, J. M. C., & Tenreyro, S. (2006). *The log of gravity*. *The Review of Economics and Statistics*, 88(4), 641–658. <https://doi.org/10.1162/rest.88.4.641>.
 53. Revi, A., Satterthwaite, D., Aragón-Durand, F., Corfee-Morlot, J., Kiunsi, R. B. R., Pelling, M., Roberts, D., Solecki, W., Gajjar, S. P., & Sverdluk, A. (2014). Towards transformative adaptation in cities: the IPCC's Fifth Assessment. *Environment & Urbanization*, 26(1), 11–28. <https://doi.org/10.1177/0956247814523539>.
 54. Shurpali, N. J. (2023). Urbanization associated changes in biogeochemical cycles. *Global Change Biology*, 29(7), 1780–1792. <https://doi.org/10.1111/gcb.16698>.
 55. Stern, D. I. (2004). The rise and fall of the Environmental Kuznets Curve. *World Development*, 32(8), 1419–1439. <https://doi.org/10.1016/j.worlddev.2004.03.004>.
 56. Stern, D. I. (2017). The Environmental Kuznets Curve after 25 years. *Journal of Bioeconomics*, 19(1), 7–28. <https://doi.org/10.1007/s10818-017-9243-1>.
 57. UN-Habitat. (2022). *World Cities Report 2022: Envisaging the Future of Cities*. United Nations Human Settlements Programme. <https://unhabitat.org/wcr>.
 58. Voukkali, I., Papamichael, I., Loizia, P., & Zorpas, A. (2024). Urbanization and solid waste production: Prospects and challenges. *Environmental Science and Pollution Research*, 30(24), 71146–71157. <https://doi.org/10.1007/s11356-023-27670-2>.
 59. Wang, J., & Wang, R. (2024). The impact of urbanization on environmental quality in ecologically fragile areas: Evidence from Hengduan Mountain, Southwest China. *Land*, 13(4), Article 503. <https://doi.org/10.3390/land13040503>.
 60. Wei, L., Cheng, Y., Wang, Z., Pan, Z., & Qi, G. (2025). Does multidimensional urbanization help reduce environmental pollution? Evidence from three major urban agglomerations in the Yangtze River Economic Belt. *Sustainability*, 17(3), Article 1202. <https://doi.org/10.3390/su17031202>.
 61. World Bank. (2024). *World Development Indicators (WDI)*. <https://databank.worldbank.org/source/world-development-indicators>.

62. Xu, Z., & Luo, J. (2025). Sustainable urbanization: Unpacking the link between urban clusters and environmental protection. *Sustainability*, 17(3), Article 873. <https://doi.org/10.3390/su17030873>.
63. Yale Center for Environmental Law & Policy. (2024). *Environmental Performance Index (EPI)*. <https://epi.yale.edu/>.
64. Zhang, X., Han, L., Wei, H., Tan, X., Zhou, W., Li, W., & Qian, Y. (2022). Linking urbanization and air quality together: A review and a perspective on the future sustainable urban development. *Journal of Cleaner Production*, 372, Article 130988. <https://doi.org/10.1016/j.jclepro.2022.130988>.
65. Zhu, T. (2025). The coupling relationship of urbanization and atmospheric environment in Shenzhen. *Theoretical and Natural Science*. Advance online publication. <https://doi.org/10.54254/2753-8818/2024.la19358>.
66. Zou, C., Zhu, J., Lou, K., & Yang, L. (2022). Coupling coordination and spatiotemporal heterogeneity between urbanization and ecological environment in Shaanxi Province, China. *Ecological Indicators*, 141, 109152. <https://doi.org/10.1016/j.ecolind.2022.109152>.

Beyond Efficiency: Understanding Job Candidates' Acceptance of AI-enabled Recruitment: A Socio-Technical Perspective

Bilal Hmoud ^{1*}, Ola Alhaddid ², George Sammour ³

¹ King Talal School for Business & Technology, Princess Sumaya University for Technology, Amman, Jordan
ORCID: 0000-0003-1685-7941
e-mail: b.hamoud@psut.edu.jo

² King Talal School for Business & Technology, Princess Sumaya University for Technology, Amman, Jordan
ORCID: 0000-0003-3631-9657
e-mail: o.alhaddid@psut.edu.jo

³ King Talal School for Business & Technology, Princess Sumaya University for Technology, Amman, Jordan
ORCID: 0000-0001-5080-8292
e-mail: george.sammour@psut.edu.jo

* Corresponding author: Bilal Hmoud, b.hamoud@psut.edu.jo

Abstract

Artificial Intelligence (AI) is increasingly reshaping recruitment processes by automating candidate screening, interviews, and hiring decisions. Despite its growing adoption, AI-enabled recruitment tools raise significant ethical and psychological concerns among job candidates, particularly regarding fairness, transparency, risk, and trust. Addressing a notable research gap concerning candidate perspectives, this study aims to investigate job candidates' acceptance of AI-enabled recruitment tools, examining how perceived usefulness, ease of use, fairness, transparency, and risk influence their attitudes, mediated by trust and moderated by AI experience. Drawing on the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Fairness, Accountability, Transparency, and Explainability (FATE) framework, the study introduces a socio-technical conceptual model to address the identified research gap. A quantitative survey was conducted with 143 job applicants in Jordan's pharmaceutical sector. The data were analysed using SPSS multiple regression analysis to assess the relationships among the variables. The findings show that perceived fairness, transparency, usefulness, and trust significantly shape positive attitudes toward AI-enabled hiring. Whereas ease of use and risk perceptions are less influential, trust proved to be a vital mediator, particularly between job applicants' perceptions of fairness and transparency and their attitudes toward AI-enabled recruitment tools, while prior AI experience moderates the influence of transparency and risk perceptions. The study concludes that respondents placed greater importance on AI's ethical and relational characteristics than technical functionality, highlighting the importance of designing functionally efficient, but also ethically responsible, fair, trustworthy, and transparent AI-enabled recruitment tools to promote candidates' acceptance and enhance responsible AI adoption in emerging labour markets.

Key words

IT adoption, AI in recruitment, trust in AI, ethical AI adoption.

Cite as:

Hmoud, B., Alhaddid, O., & Sammour, G. (2025). Beyond Efficiency: Understanding Job Candidates' Acceptance of AI-enabled Recruitment: A Socio-Technical Perspective. *Forum Scientiae Oeconomia*, 13(3), 89–113.

https://doi.org/10.23762/FSO_V OL13_NO3_4

Received: 10 January 2025

Revised: 15 July 2025

Accepted: 10 September 2025



Copyright: © 2025 by the authors. For open-access publication within the terms and conditions of the Creative Commons Attribution (CC BY) licence (<https://creativecommons.org/licenses/by/4.0/>).

Introduction

Artificial Intelligence (AI) is reshaping the future of work and continues to be the climax of contemporary digital transformation (Moravec et al., 2024). In Human Resource Management (HRM), AI is significantly altering how organisations attract, engage with, develop, and select talent. Particularly in HR recruitment and selection, AI is broadly utilised in automating its tasks such as screening applications, conducting virtual instant interviews, and performing predictive hiring decisions, resulting in enhanced efficiency and consistency of hiring decisions (Deepa et al., 2024). However, despite their promise of greater objectivity and scalability, AI-enabled recruitment systems pose essential socio-technical challenges, particularly concerning user perceptions of fairness, transparency, risk, and trust (Glikson & Woolley, 2021; Kelly et al., 2023). These concerns are critical for job candidates, whose experiences with AI systems could influence specific outcomes relevant to them, such as hiring decisions and broader judgment of legitimacy, equity, and organisational ethics (Hilliard et al., 2022; Mirowska & Mesnet, 2022).

Despite the cumulative body of literature tackling AI applications in HR recruitment, several critical gaps remain. The most notable limitation is the excessive emphasis on managerial and organisational-level perspectives, stressing algorithmic efficiency and bias mitigation from the employer's viewpoint. The literature concentrates on HR professionals, systems designers, and organisational outcomes of AI adoption, bypassing the front-end experience of job candidates whose perceptions as the primary subjects of recruitment are underrepresented (Ore & Sposato, 2022; Rigotti & Fosch-Villaronga, 2024).

Consequently, despite their critical role as primary users, there is a notably insufficient exploration of job candidates' perceptions of AI-enabled recruitment and empirical studies focusing specifically on their perspectives. This gap undermines the efforts to fully understand the human implications of AI-enabled recruitment. It creates a noteworthy gap in understanding how job candidates, particularly in developing markets, perceive and engage with AI-enabled recruitment systems. In other words, AI-driven recruitment tools are increasingly being adopted. However, our understanding of their reception by job candidates remains limited, particularly regarding trust and ethical concerns in non-Western contexts such as Jordan.

To address this gap, this study investigates candidates' perceptions of AI-enabled recruitment, particularly their perceived functionality, fairness, risk, transparency, and trust as fundamental factors key to shaping their acceptance of such systems. By incorporating ethical, functional, and contextual actors, the study integrates theoretical constructs into a candidate-centric conceptual framework from a socio-technical perspective while investigating the mediation role of trust not as merely a static predictor, but as a dynamic influence shaped by AI systems' characteristics (Bedué & Fritzsche, 2022; Wanner et al., 2022) while considering the moderating role of user familiarity and experience with AI technologies.

To achieve the study aim, we intend to accomplish the following research objectives:

1. Assess how job candidates perceive AI-enabled recruitment tools' fairness, functionality, transparency, and risk.
2. Examine the mediating role of trust in shaping candidate attitudes toward AI-enabled recruitment.
3. Explore the moderating role of AI familiarity and experience in these relationships.

Accordingly, this study addresses the following research questions:

- RQ1: How do job candidates perceive the functionality, fairness, transparency, and risk of AI-enabled recruitment tools in Jordan?
- RQ2: How does trust mediate the relationship between these perceptions and their attitude toward AI-enabled recruitment?
- RQ3: How do user familiarity and experience with AI moderate these relationships?

Grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT), the Technology Acceptance Model (TAM), and Fairness, Accountability, Transparency, and Explainability (FATE

framework) (Davis, 1989; Shin, 2020; Venkatesh et al., 2003), the study offers empirical insights from the Jordanian context, which is characterised by high youth unemployment, a challenging digital transformation setting, and a nascent interest in utilising AI tools in public and private sector hiring practices.

Drawing on data collected from the job candidates, the study offers evidence of their perceptions of AI-enabled recruitment, enriching the limited body of literature from developing non-Western labour contexts (Hu et al., 2024; Lashkari & Cheng, 2023). It advocates shifting from technologically deterministic models to socio-technical frameworks that emphasise trust-aware, ethical, and equity-focused AI design and implementation in real-world hiring settings. From a policy standpoint, the study informs Jordanian public and private institutions and technology providers about the ethical and operational prerequisites for deploying AI in employment. The study aligns with SDG 8: “Decent Work and Economic Growth”, specifically, SDG target 8.5 that endorses equal opportunity for all through the development of responsible AI tools that promote inclusive and equitable access to employment opportunities, particularly for youth and marginalised groups (Figueroa-Armijos et al., 2023; United Nations, 2015).

1. Literature review

1.1 Introduction to AI in Recruitment

AI refers to a broad set of technologies that empower systems to imitate human-cognitive functions such as reasoning, learning, and decision-making (Tambe et al., 2019; Wang, 2003) using machine learning (ML) techniques, which simulate the human brain’s capacity to process immense and complex information (Deepa et al., 2024; Wang, 2003). While minimising or neutralising human intervention, the goal is to instantaneously perform autonomous decision-making (de Visser et al., 2018) with minimal effort.

Defining AI remains contentious across academic, governmental, and public domains despite its proliferation. Many technologies referred to as ‘AI’, like smartphones or smart cars, lack the adaptive autonomy of true AI, leading to confusion around what users are actually interacting with. This definitional ambiguity or oversight complicates AI acceptance studies since users’ understanding of AI may diverge from its actual technological capabilities (Kelly et al., 2023). For clarity, AI can be categorised into three types: Artificial Narrow Intelligence (ANI), which includes most of current systems like Siri or Google Home; Artificial General Intelligence (AGI), which remains theoretical; lastly, Artificial Super Intelligence (ASI), which could one day exceed human intelligence (Bringsjord, 2011; Omohundro, 2014; McLean et al., 2020); cited in (Kelly et al., 2023).

In HRM, AI is widely adopted for continuous development and enhancing efficiency of the HRM functions through processing data collected from various external and internal sources, such as social media, job portals, performance metrics, and historical records to support recruitment, performance evaluation, training, retention, and competency mapping (Deepa et al., 2024). Particularly in recruitment, AI-enabled tools are used for screening resumes, automated interviews, and predictive hiring algorithms, which empower organisations to process an enormous number of job applications while limiting subjectivity in hiring decisions (Allal-Chérif et al., 2021; Deepa et al., 2024).

1.2 AI Role in Prompt Hiring Processes and Candidates' Experience

Adopting AI in HR recruitment processes has significantly impacted its consistency, scalability, and swiftness. For instance, it is argued that AI-enabled video interviews significantly improve the objectivity of applicant evaluation and reduce judgmental human bias (Allal-Chérif et al., 2021; Deepa et al., 2024). Chatbots and virtual assistants improve candidates' experience through instant, real-time, and personalised interactions. Additionally, Explainable AI (XAI) which refers to the degree to which an AI technology can explain its reasoning, decisions, and outputs in a way that is comprehensible to humans are being developed to boost job candidates' trust by enhancing AI's transparency, fairness, and usability in hiring decisions (Deepa et al., 2024; Robert et al., 2020).

While AI's advantages are widely recognised, its success in recruitment is dependent on end-users' perceptions and acceptance, particularly job candidates, who directly interact with AI hiring tools. While perceived usefulness, ease of use, and trust significantly influence the behavioural intention to adopt AI (Kelly et al., 2023), job candidates often question the fairness and transparency of AI decision-making, especially when interacting with automated interviews or algorithmic screening tools. Studies also suggest that perceived dehumanisation and a lack of feedback can undermine trust, even when AI appears technically efficient (Mirowska & Mesnet, 2022).

This reinforces the argument that user acceptance is highly contextual (i.e., context-sensitive nature) and cannot be detached from the cultural, demographic, and social environment in which the AI operates, as suggested by Sheng et al. (2008), who argued that technology adoption varies based on cultural and demographic contexts. A nuanced understanding of how users define and perceive AI is essential, since acceptance may be shaped not merely by the actual system characteristics but also by what individuals believe it to be (Kelly et al., 2023).

Much of the existing literature concentrates on 'managerial' competencies required for AI-HR integration, such as digital literacy, social capital, and decision-making agility (Deepa et al., 2024). However, this managerial focus often overlooks the candidate's perspective, the very individuals whose engagement contributes to the system's effectiveness. AI adoption in HRM cannot be evaluated solely on back-end efficiency; it must also consider the front-end user experience. Candidate perceptions of competence, benevolence, and integrity in AI interactions are essential to building trust and sustaining employer brand value (Kelly et al., 2023).

Furthermore, studies suggest that human oversight remains crucial in highly 'automated' systems, particularly in ethically sensitive areas such as HR recruitment (De Visser et al., 2018; Kaplan & Haenlein, 2019). Therefore, AI should not be considered as replacing human decision-making, but rather as a tool that augments inclusive and thoughtful recruitment practices. Understanding candidate acceptance enables not only the ethical deployment of AI but also its practical value across real-world recruitment scenarios.

1.3 Theoretical Foundations

Investigating candidates' perception and acceptance of AI-enabled recruitment systems necessitates a multidimensional approach that integrates functional and ethical considerations. This study is based on three main theoretical frameworks: TAM, UTAUT, and the FATE, which jointly offer a comprehensive foundation for understanding the technical, ethical, and socio-contextual factors that influence candidate acceptance of AI-enabled recruitment.

Among the earliest widely accepted information technology adoption models are TAM and UTAUT. The TAM framework (Davis, 1989) explains users' adoption of new technologies mainly using two predictors, namely, Perceived Usefulness (PU), which measures users' perception about the functional competence and Perceived Ease of Use (PEU), which reflects their perception of system usability and ease of interaction. PU and PEU positively influence attitude, which in turn is positively associated with intentions and eventually with the actual use (adoption). Meanwhile, UTAUT (Venkatesh et al., 2003) extends this premise by adding social influence, which is social pressure in the form of users' perception of whether influential others believe they should use the system. Hedonic Motivation measures the extent to which using the technology is enjoyable, and facilitating conditions reflecting individual beliefs about the organisation's technical infrastructure to support the system application (Venkatesh et al., 2003). Moreover, UTAUT incorporated mediating factors such as experience and age.

Several studies have utilised TAM and UTAUT to investigate AI adoption. PU, for instance, has been consistently considered the strongest predictor of attitude towards AI applications in HRM across sectors, which in turn positively affects their intention to adopt AI when they believe it potentially positively impacts HRM productivity, scalability and objectivity of hiring (Ibrahim et al., 2025). Further, organisational support positively influenced PU and PEU, contributing to greater augmented AI acceptance among HR professionals (Priksat et al., 2025). Another finding (Herzallah

& Makaldy, 2025) showed that PU and PEU are significantly influenced by psychological attributes such as mindset and self-efficacy. Other studies applied UTAUT to examine how individual, environmental, and technological factors influence the acceptance of AI, validating UTAUT predictors, especially effort and performance expectancy, which correspond with TAM PU and PEU (Ali et al., 2024).

Some scholars (Prikshtat et al., 2025) incorporated additional contextual variables, such as HR effectiveness and organisational support, which have proven to support TAM and UTAUT prediction of AI-enabled hiring systems adoption. Meta-analysis has shown that these constructs consistently predicted the attitude and behavioural intention toward using AI applications (Ali et al., 2024). Hence, this study hypothesises:

H1: Perceived Usefulness (PU) positively affects job candidates' Attitudes (ATT) toward AI-enabled recruitment.

H2: Perceived Ease of Use (PEU) positively affects job candidates' Attitudes (ATT) toward AI-enabled recruitment.

1.4 Candidate-Centric Constructs: FATE Framework Ethical and Relational Dimensions

While TAM and UTAUT concentrate on system usability and functionality, they neglect addressing ethical concerns. Consequently, the FATE framework (Shin, 2020) is incorporated to account for the non-functional ethical characteristics such as fairness, transparency, risk, and trust, which are critical concerns in investigating AI-enabled hiring. The FATE lens enables moving further beyond technical efficiency and examining how perceived ethical attributes of AI-enabled systems influence user acceptance and attitude (Bedué & Fritzsche, 2022; Wanner et al., 2022).

Shin's study showed that candidates are more likely to perceive it as useful, trust it, and be willing to accept AI decisions when they believe it is fair, accountable, transparent, and explainable.

Perceived fairness (PF) is the degree to which users view the decision-making processes and outcomes to be justful, which is commonly classified into procedural fairness (process fairness), distributive fairness (outcome fairness), and interactional fairness (dignity and information sharing in decision-making) (Ochmann et al., 2024; Xiong & Kim, 2025).

In HR recruitment and selection, candidates may sense AI fairness dimensions differently. Studies argued that the lack of social presence and behavioural control may decrease the job candidates' fairness perception and comfort with these tools (Hilliard et al., 2022). In other words, algorithmic systems often struggle with interactional and procedural fairness resulting from the limited transparency and the absence of human empathy (Ochmann et al., 2024). Other studies suggest that user expectations, system design, and ethical safeguards make fairness perception highly dependent on contextual features (Shin, 2020). Hence, it is essential to cite that algorithmic fairness highly depends on technical precision and users' cognitive and emotional judgments of an AI system's behaviour. This is illustrated by how users' thoughts of trust, accountability, transparency, and explainability portray a basic heuristic for engaging with and accepting personalised AI systems (Shin, 2020).

Another critical factor and complication of adopting AI in recruitment is the challenge of ethical bias. While AI is thought to eliminate human bias, resulting in more neutrality and objectivity, evidences suggest that it can learn from biased data, thus develop or even strengthen discriminatory patterns by inheriting and amplifying existing biases in historical data (Hunkenschroer & Luetge, 2022). A famous real-world illustration is Amazon's discontinued AI-enabled recruitment tool, which was shown to penalise resumes that had the word "women" or referenced only women's colleges (Dastin, 2022). Binns (2018) highlights the complexity of the concept of fairness, with contesting definitions driven by political philosophy, such as treatment equality versus outcome equality, complicating the implementation of fair AI systems in sensitive contexts.

Empirical findings have shown that XAI methods can mitigate these effects (Haque et al., 2023; Hofeditz et al., 2022; Wanner et al., 2022). Hofeditz et al. (2022) argued that increased algorithmic recommendations transparency reduces discrimination against women and older applicants.

However, they found that ‘explanation’ in AI systems could also unintentionally lower selection rates of racial minority groups, in particular when XAI is poorly contextualised.

Araujo et al. (2020) emphasised that the perceptions of fairness are contingent on the domain and affected by individual characteristics such as education, self-efficacy, experience, privacy concerns, and values. At the same time, it is worth noting that the individual disparities in accepting Automated Decision-Making (ADM) vary based on Socio-Technical factors, a distinct variation in AI-trust in low-stakes contexts, such as media, advertising, and consumer tech, versus high-stakes contexts, such as healthcare, finance, and security systems (Araujo et al., 2020).

As far as procedural justice is concerned, the literature underscores the importance of procedural justice and uncovers that granting users increased power and control over outcomes improved their perceptions of fairness, while simply explaining fairness principles did not have such an effect (Lee et al., 2019). This observation confirms Wang et al. (2020), who described a ‘favourability bias’ where individuals perceive algorithmic decisions to be fairer based on fairness-related consequences and outcomes, regardless of statistics or bias prevention measures.

Interactional fairness describes the relational component, which is often neglected in AI-enabled recruitment systems. Investigations by Kim and Heo (2021) and Nørskov et al. (2019) of AI video interviews, although being viewed as efficient and procedurally fair, candidates expressed discomfort due to the absence of social presence and human empathy. Interestingly, in some cases, job candidates rated robot-mediated interviews as fairer than human ones, implying that their impartiality and objectivity perception could outweigh or offset the lack of connectivity; however, this is not a common presumption among HR professionals who emphasise efficiency over ethical equity.

Ochmann and Laumer (2019) assert that when determining whether to adopt or trust AI in hiring, stakeholders evaluate fairness from multiple dimensions: ethical alignment, explainability, diversity, inclusion, and non-discrimination. Teodorescu et al. (2021) framing goes beyond technical fairness metrics to sociotechnical frameworks that ground fairness strategies to particular recruitment and users’ contexts, proclaiming that the best path to fairness is through augmented human–AI methods such as informed reliance and proactive oversight. Hence, AI and humans are required for fairness, and neither one alone could guarantee fairness.

These insights indicate that the fairness of AI-enabled recruitment systems and interventions should be multi-dimensionally conceptualised, covering system ethical perspectives (bias mitigation, XAI), procedural justice, user transparency, and socio-emotional dimensions. Once these issues are addressed, AI systems can earn legitimacy and trust that can eventually move the dial on candidates’ behavioural outcomes, including application intent, engagement, and advocacy. Consequently, the study hypothesises the following:

H3: Perceived Fairness (PF) positively affects job candidates’ Attitudes (ATT) toward AI-enabled recruitment.

AI transparency is a key building block to establish trust and promote positive user perception (Bedué & Fritzsche, 2022; Felzmann et al., 2019; Glikson & Woolley, 2020). Compared to prior technologies, AI systems’ complexity, social implications, and unpredictability make trust-building a much more nuanced endeavour. Utilising the Extended Valence Framework, based on semi-structured interviews with professionals, Bedué and Fritzsche (2022) found transparency and explainability to be essential sub-dimensions, which allow for the delivery of meaningful insights into how AI systems operate.

The legal frameworks provide further context for understanding the role of transparency in AI adoption. Felzmann et al. (2019) identify and analyse two key components of transparency: prospective transparency, meaning information provided prior to a decision being made (the use of applicant data, for example), and retrospective transparency, which includes post-hoc explanations (such as the reasons for candidate rejection). It offers a relational perspective to transparency by arguing that the information provision should be understood as a type of communicative act occurring between AI developers and users (e.g., through interactive visual cues, amongst others) that

is contingent upon contextual factors, including user literacy, industry standards, technical requirements, etc. In recruitment, this means moving from passive disclosure to engaged, user-centred design that allows both candidates and hiring professionals to interrogate and understand AI decisions.

Moreover, AbdulKareem et al. (2024) examine the adoption of ICT and social media tools for e-recruitment in Nigeria's federal public sector. Their findings demonstrate that ICT adoption enhances transparency, trust, and efficiency in recruitment systems, particularly when supported by digital literacy. They also recognise internet self-efficacy as a moderator variable, and argue that users who feel more confident about their digital skills are more likely to have a positive perception of the transparency and trustworthiness of the recruitment systems. This underlines the need for capacity building and user training initiatives complementary to the adoption of IT in HR recruitment.

Angerschmid et al. (2022) studied how transparency has the potential to repair or enhance trust through the effects of fairness levels and types of transparency on AI-augmented decision-making. Their users' study showed that low perceptions of fairness and transparency do indeed decrease trust significantly. However, the inclusion of fairness and transparency based on feature importance or case-based reasoning can help reestablish some trust (Angerschmid et al., 2022). These issues are acute in a recruitment setting, where perceived decision-making bias or lack of transparency may result in potential candidates disengaging from the process or reputational damage for the organisations involved.

Another perspective is 'algorithmic vigilance' (Zerilli et al., 2022), a middle-of-the-road approach where users critically interact with AI outputs rather than rejecting them utterly, conceptualise trust in AI as a spectrum, with aversion (unwarranted scepticism) on one end and appreciation or loafing (uncritical overreliance) on the other. The findings underscore the importance of implementing task-sensitive and fixable strategies that address the users' needs and deliberate the decision-making contexts, such as HR recruitment. Consequently, AI-enabled recruitment systems should provide explanatory information and additional indicators, such as performance metrics, confidence levels, and error rates, to enable users to make well-informed and critically evaluated judgments about AI transparency.

These literatures provide strong, cohesive evidence that perceived transparency is essential in positively shaping users' trust, attitudes toward AI, and intentions to engage with AI systems. Moreover, transparency should not be confined to technical disclosures; it must enable users to comprehend, critically engage with, and eventually trust AI-driven decisions by offering dynamic, communicative, and context-sensitive transparency, which in turn positively influences their attitude (Xiong & Kim, 2025). Accordingly, the study hypothesises the following:

H4: Perceived Transparency (PT) positively affects job candidates' Attitudes (ATT) toward AI-enabled recruitment.

Integrating AI with recruitment processes will likely raise perceived risk concerns, influencing users' trust and attitude (Araujo et al., 2020; Lashkari & Cheng, 2023; Li, 2025). Perceived risk is commonly considered to have a significant negative impact on the perception of users' attitude and intention of technology adoption. It could weaken the effects of ease of use and perceived usefulness while amplifying the role of subjective norms (Chaudhary, 2024). In AI hiring, the perceived risk also involves apprehensions regarding algorithmic bias, fairness, transparency, loss of intuitive human judgment and that which influences trust and acceptance of these tools.

Moreover, Araujo et al. (2020) explored how AI fairness, usefulness, trust, and risk perceptions fluctuate across sectors (e.g., public health, media, and justice). Their findings showed that these factors are highly subject to individual characteristics and the contextual aspects (Larsson et al., 2024). The context-specific evidence shows that some participants showed agreeableness to rely on AI-driven output equivalent to human decisions in low-stakes contexts; on the other hand, scepticism prevailed in high-stakes contexts.

In the given context of recruitment, by interviewing recruiters and job candidates, Lashkari and Cheng (2023) investigated the phenomenon of AI-enabled recruitment, possible misjudgement, bias, and the absence of human interaction. The findings revealed that while job seekers emphasised the necessity of relationship-building, fairness, and human-centred interactions, recruiters focused on the cognitive bias and a desire for supportive technologies. These findings highlight the risk-trust dynamic, which in turn shapes the user's acceptance and intentions toward these AI-enabled recruitment methods.

Although focused on system design perspectives, empirical investigation of Li (2025) reinforced these conclusions and found that perceived anxiety and risk exert a significant adverse effect on system designers' intentions to adopt AI-generated content (Rigotti & Fosch-Villaronga, 2024). These findings can be extrapolated to the recruiting context where perceived risk erodes trust and, in turn, negatively impacts the likelihood of a candidate's acceptance of AI-enabled recruitment.

The existing literature across different disciplines confirms the adverse effect of perceived risk in AI systems acceptance, particularly in high-stakes contexts such as recruitment. Accordingly, the study hypothesis:

H5: Perceived Risk (PR) negatively affects job candidates' Attitudes (ATT) toward AI-enabled recruitment.

Although often used interchangeably in technology adoption literature, to further explain the conceptual design of this study, it is crucial to conceptually and theoretically distinguish between trust in AI and attitude toward AI-enabled recruitment systems, given their distinct roles in shaping job candidate acceptance. Trust in AI is a multi-faceted, belief-based construct that represents a user's perspective on how much they can and are willing to rely on an AI system in situations of uncertainty or vulnerability (Glikson & Woolley, 2020; Lee, 2018). Trust is known to be based on the perception of system competence, integrity, and benevolence (Bedué & Fritzsche, 2022; Mayer et al., 1995). Therefore, in this study context, trust implies that the user believes that the AI-enabled recruitment functions operate with competence, integrity, and benevolence and are in accordance with ethical expectations, even without granting complete transparency or control.

In contrast, attitude toward AI is another wider form of judgment as a general evaluation of users' positive or negative feelings about using technology (Davis, 1989, 2023; Li, 2025), which in this study context, is AI-enabled recruitment tools. Attitude is an affective-cognitive disposition that includes beliefs, emotions (e.g., comfort, anxiety), and behavioural tendencies (e.g., willingness to accept AI decisions).

Trust in AI is a multi-faceted, belief-based construct that represents a user's perspective on how much they can and are willing to rely on an AI system in situations of uncertainty or vulnerability (Glikson & Woolley, 2020; Lee, 2018). Trust is known to be based on the perception of system competence, integrity, and benevolence (Bedué & Fritzsche, 2022; Mayer et al., 1995). Therefore, in this study context, trust implies that the user believes that the AI-enabled recruitment functions operate with competence, integrity, and benevolence and are in accordance with ethical expectations, even without granting complete transparency or control.

In contrast, attitude toward AI is another wider form of judgment as a general evaluation of users' positive or negative feelings around using technology (Davis, 1989, 2023; Li, 2025), which in this study context, is AI-enabled recruitment tools. Attitude is an affective-cognitive disposition that includes beliefs, emotions (e.g., comfort, anxiety), and behavioural tendencies (e.g., willingness to accept AI decisions). Literature often assumes that trust is a predictor or mediator that influences attitudes (Shin, 2020). In summary, trust is a focused belief regarding the technology's reliability, functional competence, and integrity, while attitude is a wider disposition towards interacting with that system.

This conceptual differentiation allows for a more precise examination of the pathway, where perceived fairness and transparency boost trust, which in turn positively shapes attitude toward AI-enabled recruitment. Such a pathway has been supported in empirical studies by Wanner et al. (2022), Xiong and Kim (2025), and Shin (2020), who emphasise the mediating role of trust in technology

acceptance, particularly in ethically sensitive domains like hiring. Establishing this distinction between trust theory and attitude enhances the conceptual framework's explanatory clarity and empirical robustness.

When investigating the adoption and acceptance of AI in HRM, trust has been identified as a key construct (Bedué & Fritzsche, 2022; Figueroa-Armijos et al., 2023; Lee, 2018; Rukadikar & Khandelwal, 2024; Wanner et al., 2022). From initial resume screening to final-phase interviews, AI systems are progressively becoming integrated into recruitment processes. The effectiveness of such tool's hinges not only on their technical competence but also on the extent to which users trust them. The notion of trusting the process is at its core based on the principle of perceived transparency, which emerged as a normative ethical expectation and a determinant of acceptance and engagement (Ogunniye et al., 2021). Bedué and Fritzsche (2022) shed light on the need for self-imposed standards and multi-stakeholder responsibility, particularly in high-impact areas such as recruitment, suggesting that trust has three interrelated dimensions: competence, integrity, and benevolence.

In their contribution, Glikson and Woolley (2020) conducted a multidisciplinary review of empirical research on AI trust. They distinguish cognitive trust from perceptions of the AI system's reliability, responsiveness and transparency, and emotional trust shaped by anthropomorphising traits and perceived intent. This two-tiered model of collation trust is present in recruitment, where job seekers and HR professionals desire both procedural clarity and emotional assurance of AI decision-making that aligns with human values and is devoid of implicit biases. Rukadikar and Khandelwal (2024) argued that while HR professionals generally trust AI-enabled tools like chatbots, data privacy and cultural alignment persist as obstacles. Thus, the study hypothesis:

H6: Trust in AI (TRS) positively affects job candidates' Attitudes (ATT) toward AI-enabled recruitment.

Moreover, trust might mediate between perceptions of AI characteristics, such as fairness, transparency, and explainability, and job candidates' attitudes toward it (trust-outcome relations). Several empirical studies confirm the intermediary role of trust (Ogunniye et al., 2021). Job candidates' trust increases when AI systems are generally perceived as transparent and fair, and AI perceived risk diminishes, resulting in more positive attitudes towards the organisation and hiring process. Moreover, trust mediates the relationship between AI explainability and candidate receptiveness, especially if the system is clear on "how" and "why" explanations (Xiong & Kim, 2025).

Consistent with this proposed mediating effect, Shin (2020) found that candidates who perceived AI systems as accountable and transparent exhibited increased satisfaction and engagement. Wanner et al. (2022) adopted a UTAUT-based model and found that transparency increases trust, which in turn enhances performance perception and adoption possibilities. Likewise, Bedué and Fritzsche (2022) stressed that trust, defined by the competence, integrity, and benevolence perceptions, plays a mediating role between transparency and the behavioural intention of adoption.

Ethical and organisational factors also contribute to trust. Figueroa-Armijos et al. (2023) associated performance expectancy with ethical perceptions of the AI, hence supporting organisational trust. From this perspective, the study hypothesis:

H7: Trust (TRS) in AI mediates the relationship between Perceived Fairness (PF) and Attitude (ATT) toward AI-enabled recruitment.

H8: Trust (TRS) in AI mediates the relationship between Perceived Transparency (PT) and Attitude (ATT) toward AI-enabled recruitment.

H9: Trust (TRS) in AI mediates the relationship between Perceived Risk (PR) and Attitude (ATT) toward AI-enabled recruitment.

Taken together, these findings demonstrate that trust in AI-recruitment is multi-dimensional and is shaped by system attributes (e.g., competence, integrity, and benevolence), contextual factors (e.g., organisational readiness, culture), and user perceptions (AbdulKareem et al., 2024; Angerschmid et al., 2022; Haque et al., 2023). Future research is needed to further clarify the complex pathways of

trust's impact on AI acceptance and adoption while considering the contextual attributes in culturally diverse and ethically sensitive domains.

Although trust is assumed to mediate user attitudes toward AI in recruitment, their experience with AI can also act as a moderating factor shaping the extent to which perceived ease of use, trust, and other constructs influence their attitude towards AI. Studies conducted in culturally diverse settings highlighted digital exposure as a significant moderating factor (Upadhyay & Khandelwal, 2018).

Grounded on the extended UTAUT model, Tanantong and Wongras (2024) and Wongras and Tanantong (2023) investigated AI-enabled recruitment in Thailand. Their findings revealed earlier exposure or familiarity with AI technologies moderated the effect on effort expectancy and perceived usefulness. Ismatullaev and Kim (2022) confirmed these findings, showing that trust, fostered by transparency and simplicity, significantly enhances usability perceptions. Thus, this relation is even more substantial among users with AI experience. On the other hand, Glikson and Woolley (2020), in their two decades of research review, underlined that cognitive and emotional trust are driven by system anthropomorphism, reliability, and the context of use, which are factors that are more striking among experienced users.

In experimental research, Lee (2018) found that although people perceived algorithmic decisions as efficient, they were less trusted than human decisions, especially in empathy-demanding roles. These findings suggest that familiarity is imperative in relation to expectations, social norms, and perceived risks. Further, ease of use, perceived fairness, transparency, and explainability are some of the main domains in which user experience interferes with acceptance. Studies by Haque et al. (2023) and Angerschmid et al. (2022) showed that users' previous exposure to AI would enhance their responsiveness to clear, human-like instructions, hence showing more acceptance. From this viewpoint, the study hypothesis:

H10: AI Experience moderates the relationship between Perceived Ease of Use (PEU) and Attitude (ATT) toward AI-enabled recruitment, such that the relationship is stronger among those with higher experience.

H11: AI Experience moderates the relationship between Perceived Fairness (PF) and Attitude (ATT) toward AI-enabled recruitment, such that the relationship is stronger among those with higher experience.

H12: AI Experience moderates the relationship between Perceived Transparency (PT) and Attitude (ATT) toward AI-enabled recruitment, such that the relationship is stronger among those with higher experience.

H13: AI Experience moderates the relationship between Perceived Risk (PT) and Attitude (ATT) toward AI-enabled recruitment, such that the relationship is stronger among those with higher experience.

1.5 Justification for the Proposed Framework: Integrated Socio-Technical Framework

When investigating HR recruitment through controversial means such as AI, it is crucial to note that attitudes are hardened by concerns over fairness, risk, loss of human touch, and algorithmic ambiguity, provoking scholars to integrate trust and other social factors as predictors or mediating variables. Such a holistic approach enhances our understanding of adoption phenomena through a similar predictive intersection of TAM and UTAUT characteristics.

While TAM and UTAUT models have been widely applied in explaining the adoption and acceptance of AI across organisational settings (Ore & Sposato, 2022; Rigotti & Fosch-Villaronga, 2024), this study considers their constructs from a user-centric perspective, specifically, job candidates. Contrasting organisations, employees or managers who may be introduced appropriately, receive training or other organisational support to adopt IT systems, job candidates' experience with AI-enabled recruitment systems is mostly a one-time, consequential interaction that lacks institutional support. Therefore, this context mandates expanding the earliest models to incorporate social and ethical constructs which are under-theorised in early technology adoption theories.

Consequently, grounded on TAM, UTAUT, and FATE literature, this study addresses these gaps by proposing an integrative framework (Figure 1).

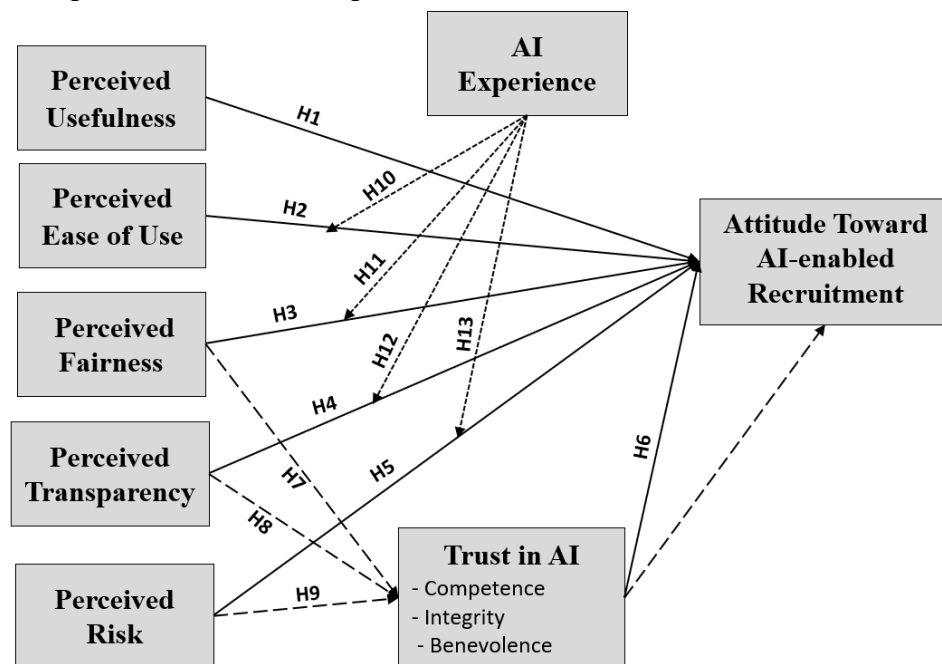


Figure 1. Study Framework.

Note: Solid line for direct effects (H1–H6), dashed line for mediation effects (H7–H9), dotted line for moderation effects (H10–H13).

Source: Author's elaboration.

This framework is well-suited to achieve the study objectives and capture the candidate perspective by exploring how perceived usefulness, ease of use, and external variables, namely perceived fairness, transparency, risk, and trust, influence job candidates' attitudes toward AI-enabled recruitment. Meanwhile, introducing trust as a fundamental mediating variable and experience as a moderator, the framework facilitates the explanation of variations in candidate acceptance that traditional models have not fully addressed.

This enhanced framing contributes to the academic literature as it further bridges the gap by re-centring the focus on candidates whose perspective is often neglected in AI adoption research. It also contributes to theoretical integration by combining perceptual and behavioural constructs in recognised technology acceptance models. The framework offers organisations a structured guide to designing transparent, ethical, and user-friendly AI-enabled recruitment systems which are more likely to be trusted and accepted by job applicants.

2. Methodology

2.1 Instrument and Data Collection

Considering this study's exploratory and descriptive nature, a questionnaire-based quantitative research approach was employed. An online questionnaire following Sekaran and Bougie's (2016) recommendations was developed and administered among job applicants. The questionnaire's primary objective was to measure applicant attitudes and trust toward AI-powered tools in recruitment processes, particularly in screening and assessment contexts.

The questionnaire had two sections. The first collected demographic and sample characteristics, namely respondents' age (measured in terms of four age categories), educational level (four educational levels), and professional work experience (four experience scales). Besides, respondents' AI experience was measured using a structured single-item measure for which four clearly defined experience levels: "No Experience" (never used or directly interacted with AI technologies); "Limited Experience" (minimal or short-term familiarity and interaction with AI, for instance, occasional use);

"Moderate Experience" (recurring regular interaction and familiarity about basic AI capabilities, for example, generative AI, AI assistants, or chatbots); and "Extensive Experience" (high-frequency interaction and significant familiarity or occupational use of sophisticated AI tools). These items provided contextual and demographic information about respondents' backgrounds, where some are supposed to potentially affect their attitudes toward AI in the recruitment context.

The second section comprised structured items that measure the core constructs of the study, specifically a total of eight key constructs measured using 28 items. All construct items were scaled on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). These measurement items are grounded on previously validated instruments used in the existing literature (see Table 1) and were revised and reworded minimally to fit this study's contextual and cultural context.

The constructs measures comprised Perceived Usefulness (PU), which was measured using three items measuring respondents' perception of AI's efficiency, accuracy, and quality in processing recruitment decisions; Perceived Ease of Use (PEU), which comprised three items measuring simplicity, user-friendliness, and ease of interaction with AI-powered recruitment tools; Perceived Fairness (PF), comprised three items measuring respondents' perception of AI impartiality and equally in recruitment decision; Perceived Transparency (PT), formed three items reflecting respondents' perception about the clarity and simplicity of AI's decision-making process; and Perceived Risk (PR), which was measured using three items assessing respondents' perception of data privacy, evaluation error, and misjudgement of AI-enabled recruitment.

Trust in AI (TRS) was conceptualised with three subdimensions: Competence, Beneficence, and Integrity (McKnight et al., 2002), each measured using three items. These subdimensions captured the respondents' trusting belief in AI's ability, ethical intentions, and reliability. Lastly, Attitude Toward AI in Recruitment (ATT) was measured using four items reflecting respondents' overall conception of the position and acceptance of AI-enabled recruitment decisions.

The questionnaire was developed in English and checked by HRM and information systems experts. A small sample pilot test was carried out to evaluate the instrument's coherence and clarity, which resulted in minor changes and improvements based on the feedback. The data were collected over a six-week period through a Google Forms link that was shared with job candidates through emails by hiring professionals involved in the recruitment process and who had access to the job candidates fitting the study criteria.

Table 1. Survey Constructs and References.

Construct	Items	Source(s)
Perceived Usefulness (PU)	3	Davis (1989); Venkatesh and Davis (2000)
Perceived Ease of Use (PEU)	3	Davis (1989); Venkatesh and Davis (2000)
Perceived Fairness (PF)	3	Shin (2020)
Perceived Transparency (PT)	3	Shin (2020); Langer et al. (2021)
Perceived Risk (PR)	3	Pavlou (2003); Shin (2020)
Trust in AI (TRS) – subdimensions:	9	
Competence	3	McKnight et al. (2002); Mayer et al. (1995); Glikson and
Benevolence	3	Woolley (2020)
Integrity	3	
Attitude Toward AI-enabled Recruitment (ATT)	4	Venkatesh et al. (2003)

Note: All items were adapted and reworded to reflect the context of AI-enabled recruitment.

Source: Author's elaboration.

2.1 Population and Sampling

Since this study investigates the notion of AI acceptance from the perspective of job candidates, the target population for this study comprised job applicants who had applied for job openings in three pharmaceutical companies in Jordan that employ sourced AI-enabled tools in their recruitment to process applicants' screening and evaluation processes and was carried out in December 2024. Specifically, the study targeted applicants for four different job positions, of which two were entry-

level, namely logistics coordinator and pharmaceutical sales representative, and two were mid-level openings that require four years or more of professional experience in a similar role, namely Quality Assurance (QA) specialist and IT business analyst. The approximate number of total applicants was 1,056 for the four positions representing the accessible population for the study. Due to the practical restrictions associated with reaching job applicants directly, a convenient sampling method was adopted. The study questionnaire was shared by hiring professionals of participating companies through email. The correspondence included a cover letter outlining the study's purpose and objectives while asserting anonymous voluntary participation, explaining that their responses would only be utilised for research purposes. To avoid bias and ensure that responses reflected applicants' genuine perceptions while isolating the influence of hiring outcomes, the study was administered prior to the point at which applicants were notified about their employment decision outcome.

1.3 Sample Characteristics

A total of 143 valid responses were retained for the final data analysis. As shown in Table 2, the most significant proportion of respondents was below 25 years (51.7%), followed by 26–30 years (30.8%), and 30–40 years (14.0%), while merely 3.5% were 40+ years.

Table 2. Sample Characteristics.

Variable	Categories	Frequency	Percent
Age	Less than 25 years	74	51.7
	26–30 years	44	30.8
	30–40 years	20	14.0
	40 or older	5	3.5
Education	Bachelor	104	72.7
	Master/High Diploma	38	26.6
	Doctorate	1	0.7
Work Experience	None to less than 1 year	61	42.7
	2 - 5 years	42	29.4
	6 - 10 years	32	22.4
	10 Years and Above	8	5.6
Experience with AI	No Experience	8	5.6
	Limited Experience	32	22.4
	Moderate Experience	71	49.7
	Extensive Experience	32	22.4

Source: Author's elaboration.

In terms of academic qualifications, 72.7% of respondents held a bachelor's degree, 26.6% had a master's degree, while only 0.7% had a doctoral degree. Regarding work experience, the majority of respondents (42.7%) had minimal experience, with none to less than one year of experience. Additionally, 29.4% of respondents reported having 2 to 5 years of experience, and 22.4% had 6–10 years of experience. Lastly, only 5.6% of respondents reported over 10 years of experience, representing the smallest group. Moreover, the sample distribution in terms of respondents' experience level with AI differed significantly. The largest proportion (49.7%) reported moderate experience with AI technologies, while minimal and intensive experience with AI technologies occurred equally, representing 22.4% of the study sample. The smallest group are those who reported no prior experience in AI technologies, at 5.6%. The entry and mid-level targeted job openings can rationalise this result.

1.4 Perception Differences Based on Demographics

As shown in Table 3, to examine the difference in perceptions of AI-enabled recruitment systems across demographic groups, specifically age, education level, and AI experience, one-way ANOVA tests were conducted on the framework key constructs: PU, PEU, PF, PT, PR, TRS, and ATT.

Table 3. One-Way ANOVA Results on Perceptions of AI-enabled Recruitment.

Construct	Age P-value	Education P-value	AIE P-value	AIE F-value	AIE Effect
PU	0.933	0.933	0.000	50.005	Large
PEU	0.813	0.813	0.000	50.943	Large
PF	0.34	0.34	0.000	71.244	Large
PT	0.89	0.89	0.000	53.037	Large
PR	0.65	0.65	0.000	6.825	Moderate
TRS	0.433	0.433	0.000	66.597	Large
ATT	0.571	0.571	0.000	95.844	Large

Source: Author's elaboration.

The analysis revealed the absence of statistically significant differences across the constructs based on age or education level. The p-values of all constructs were greater than the 0.05 threshold, indicating that respondents had similar perceptions regardless of their age or education level.

In contrast, for respondents' prior AI experience level, the analysis showed statistically significant differences across all with p-values less than $p < .001$. Tukey HSD tests revealed that individuals with more AI experience reported higher levels of PU, PEU, PF, PT, TRS, and ATT, along with lower levels of PR when compared to those with less or no experience.

Findings support the hypothesized moderating effect of AI experience on perceptions, implying that greater exposure and familiarity with AI may decrease scepticism and enhance acceptance, especially regarding AI-enabled recruitment perceived fairness, risk, and trust.

1.5 Measurement of Reliability and Validity

To assess the instrument's robustness and consistency, the constructs' convergent validity and internal consistency were examined. For convergent validity, a Confirmatory Factor Analysis (CFA) was performed, extracting factor loadings, Average Variance Extracted (AVE), and Composite Reliability (CR). In line with recommendations of methodological soundness (Hair et al., 2019; Chin, 1998), factor loadings with values greater than 0.50 were considered acceptable. Meanwhile, loading values over 0.7 are deemed ideal (Straub, 1989). Likewise, CR and AVE values beyond 0.80 and 0.50, respectively, are considered acceptable (Hair et al., 2019).

As shown in Table 4, item loadings exceeded the ideal threshold of 0.7. The CR values ranged from 0.882 to 0.958, while the AVE values ranged from 0.714 to 0.814. These results provide strong evidence of convergent validity across all measured constructs.

Table 4. Reliability and Convergent Validity.

Construct	Item	Loading	CR	AVE	Cronbach's α
Perceived Usefulness (PU)	PU1	0.87	0.914	0.780	0.859
	PU2	0.88			
	PU3	0.89			
Perceived Ease of Use (PEU)	PEU1	0.88	0.904	0.758	0.842
	PEU2	0.87			
	PEU3	0.86			
Perceived Fairness (PF)	PF1	0.89	0.929	0.814	0.884
	PF2	0.90			
	PF3	0.92			
Perceived Transparency (PT)	PT1	0.87	0.882	0.714	0.797
	PT2	0.89			
	PT3	0.77			
Perceived Risk (PR)	PR1	0.89	0.927	0.810	0.882
	PR2	0.90			
	PR3	0.91			
Trust in AI (TRS)	COM1	0.83	0.958	0.718	0.950
	COM2	0.86			
	COM3	0.85			
	BEN1	0.91			

	BEN2	0.87			
	BEN3	0.84			
	INT1	0.79			
	INT2	0.80			
	INT3	0.85			
Attitude (ATT)	ATT1	0.83	0.932	0.773	0.953
	ATT2	0.89			
	ATT3	0.90			
	ATT4	0.90			

Source: Author's elaboration.

Cronbach's alpha coefficients were extracted to assess the instrument's internal reliability. According to the accepted standards, values over 0.70 indicate a strong reliability (Hair et al., 2019). All constructs demonstrated Cronbach's alpha values ranging from 0.797 to 0.953, confirming the instrument's internal consistency.

Moreover, Fornell and Larcker's (1981) criterion was utilised to evaluate discriminant validity by comparing the square root of the construct's AVE with its correlations to other constructs. As shown in Table 5, the square root of the AVE exceeded its intra-construct correlations, with one exception.

Table 5. Discriminant Validity.

	PU	PEU	PF	PT	PR	TRS
PU	0.883					
PEU	0.866**	0.871				
PF	0.863**	0.850**	0.902			
PT	0.566**	0.570**	0.619**	0.845		
PR	-0.264**	-0.258**	-0.280**	-0.017	0.900	
TRS	0.821**	0.869**	0.863**	0.647**	-0.184*	0.847
ATT	0.859**	0.857**	0.891**	0.664**	-0.266**	0.877**

Note: *. Correlation is significant at the 0.05 level (2-tailed); **. Correlation is significant at the 0.01 level (2-tailed).

Source: Author's elaboration.

The TRS and ATT correlation was found to be 0.877, exceeding the square root of AVE for Trust constructs (0.847). As a result, this suggests a minor violation of the Fornell-Larcker criterion and possible overlap between the constructs. However, this finding is understandable in the context of the fundamental theory guiding the model. Trusting AI in recruitment is hypothesised to be a powerful prior condition for the individuals' attitude toward it. Thus, a robust correlation between the two constructs is not only anticipated but also theoretically well-grounded. Participants who trust AI systems in processing recruitment decisions may also rate them more positively and have highly aligned trust and attitude perceptions.

Additionally, respondents may have viewed their trust in AI as a fundamental component of their overall attitude, particularly when the assessment was performed through such technologies. This proximity of concepts might explain the higher correlation. Even though they crossed a statistical threshold, conceptually, they are still distinct constructs developed and measured with different, validated items.

Except for this single violation of Fornell and Larcker's (1981) criterion, the results confirm that the measurements show adequate discriminant validity and are perceived as empirically distinct constructs by the respondents.

3. Research results

3.1 Direct Effects

Hypotheses H1 to H6 relating to the direct effects of the presumed independent variables on the dependent variable, namely attitude toward AI-enabled recruitment (ATT), were tested using

multiple regression using SPSS. As shown in Table 6, the overall R^2 for the model is 0.867, indicating that the six predictors explain 86.7% of the variance of the dependent variable (ATT).

Table 6. Model Summary

Model	R	R^2	Adjusted R^2	Std. Error
1	0.931a	0.867	0.861	0.37323756

Note: a. Predictors: (Constant), TRS, PR, PT, PU, PEU, PF.

Source: Author's elaboration.

Table 7 summarises the regression results for each hypothesis. As exhibited, Perceived Fairness (PF) had the most potent effect on ATT ($\beta = 0.318$, $t = 4.172$, $p < 0.001$), supporting H3. Likewise, Trust in AI (TRS) had a highly positive effect on attitude ($\beta = 0.253$, $t = 3.351$, $p = 0.001$), thereby supporting H6.

Table 7. Regression Results.

Hypothesis	Construct	R2	B	T-value	Sig.	Result
H1	Perceived Usefulness (PU)	0.738	0.194	2.715	0.007	Supported
H2	Perceived Ease of Use (PEU)	0.730	0.112	1.469	0.144	Not Supported
H3	Perceived Fairness (PF)	0.796	0.318	4.172	<0.001	Supported
H4	Perceived Transparency (PT)	0.443	0.128	3.023	0.003	Supported
H5	Perceived Risk (PR)	0.071	-0.048	-1.439	0.152	Not Supported
H6	Trust in AI (TRS)	0.768	0.253	3.351	0.001	Supported

Source: Author's elaboration.

Moreover, H2 is supported where Perceived Usefulness (PU) showed a significant positive effect ($\beta = 0.194$, $t = 2.715$, $p = 0.007$), Hypothesis H4 is also supported ($\beta = 0.128$, $t = 3.023$, $p = 0.003$), where Perceived Transparency (PT) has a moderate yet significant effect. In contrast, Perceived Ease of Use (PEU) ($p = 0.144$) and Perceived Risk (PR) ($p = 0.152$) effects were insignificant at the 0.05 level, thus rejecting H2 and H5. The findings highlight that fairness, trust, usefulness, and transparency influence candidates' attitudes toward AI-enabled recruitment. Conversely, ease of use and perception of risk appear less compelling, given this study's scope.

3.2 Mediation Effects

To evaluate whether TRS mediates the relationships between the predictors (PF, PT, and PR) and the independent variable (ATT), the PROCESS Macro Model 4 (Hayes, 2022) was employed with 95% confidence and 5,000 bootstrap samples. Summarised in Table 8, the indirect effect of PF and PT on ATT through TRS is significant (IE = 0.3595; 95%, CI 0.2198, 0.5431; IE = 0.4985; 95%, CI 0.3557, 0.6501, respectively), yet the direct effect is significant, which suggests a partial mediation effect and supports H7 and H8 (Table 5).

Table 8. Mediation Effect Summary.

Hypothesis	Path	IE	LLCI	ULCI	Mediation	Result
H7	PF $\rightarrow$ TRS $\rightarrow$ ATT	0.3595	0.2198	0.5431	Partial	Supported
H8	PT $\rightarrow$ TRS $\rightarrow$ ATT	0.4985	0.3557	0.6501	Partial	Supported
H9	PR $\rightarrow$ TRS $\rightarrow$ ATT	-0.1581	-0.3221	0.0862	No Mediation	Not Supported

Source: Author's elaboration.

This result demonstrates that while PF and PT had a significant direct effect on ATT, they also improved through the increased TRS. In contrast, the indirect effect of PR through TRS was insignificant (IE = -0.1581; 95% CI -0.3221, 0.0862), implying the absence of a mediating role of TRS in the PR-ATT relationship.

Overall, the results reveal that trust is a key mediating factor in shaping candidates' attitudes towards AI-enabled recruitment, specifically the perceived fairness and transparency of such AI tools.

3.2 Moderation Effects

To examine the AI-Experience (AIE) moderating role among the predictors, namely perceived ease of use ($PEU \times AIE$), perceived fairness ($PF \times AIE$), perceived transparency ($PT \times AIE$), perceived risk ($PR \times AIE$), and the attitude toward AI in recruitment, PROCESS Macro Model 1 was used. As shown in Table 9, the interaction effects of ($PEU \times AIE$) and ($PF \times AIE$) were not statistically significant ($p = 0.1725$ and $p = 0.2553$, respectively).

Table 9. Moderation Effects Summary.

Hypothesis	Moderation Path	Interaction p-value	Moderation Effect	Result
H10	$PEU \times AIE \rightarrow ATT$	0.1725	Not significant	Not Supported
H11	$PF \times AIE \rightarrow ATT$	0.2553	Not significant	Not Supported
H12	$PT \times AIE \rightarrow ATT$	0.031	Significant	Supported
H13	$PR \times AIE \rightarrow ATT$	0.0138	Significant	Supported

Source: Author's elaboration.

Thus, H10 and H11 are not supported. The results imply that the candidates' experience with AI does not significantly intervene in the effect of ease of use and fairness perceptions on their attitudes toward AI-enabled recruitment.

In contrast, H12 and H13 yielded strong moderation effects. The perceived transparency ($PT \times AIE$) experience interaction was significant at ($p = .0310$), suggesting that the effect of perceived transparency (PT) on attitude becomes stronger among candidates with higher AI familiarity and experience. Similarly, AI Experience moderated the negative effect between perceived risk ($PR \times AIE$) and attitudes toward AI-enabled recruitment ($p = .0138$). This means that for candidates with less AI experience, perceived risk had a stronger negative effect on their attitudes toward AI-enabled recruitment. However, this effect becomes weaker or natural when candidates are highly familiar with AI. Hence, accepting H12 and H13.

4. Discussion

The results offer both expected confirmations of existing literature and novel contributions that deepen the understanding of a candidate-centred AI-enabled recruitment acceptance.

The strong effect of trust as a direct predictor is consistent with prior findings and the increasing consensus in the AI literature on the notion that trust is a gateway to user acceptance (Bedué & Fritzsche, 2022; Shin, 2021), especially in sensitive contexts such as evaluating job applications and hiring decisions. This result aligns with Glikson and Woolley's (2020) and Wanner et al.'s (2022) assertion that trust in AI extends beyond technical functionality and encompasses integrity and fairness perceptions, also confirming trust as a dynamic construct sensitive to system attributes.

Similarly, the confirmed positive effect of perceived usefulness on a candidate's attitude validates the core TAM assumption (Davis, 1989). This finding confirms Prikshat et al. (2025) and Herzallah and Makaldy (2025), who also emphasised the role of perceived usefulness in predicting attitude toward using AI.

Interestingly, ease of use did not significantly appear to predict attitudes toward AI-enabled recruitment tools. Although ease of use is frequently cited as a primary antecedent in TAM literature (Davis, 1989), this result questions whether that system-user interaction maintains its conventional significance as an IT adoption predictor. This factor may be lessening in AI contexts such as Chatbots, Generative AI, or AI-enabled hiring tools, where complexity is lower and users' interaction with the system interface is effortless and limited.

Interestingly, perceived risk did not significantly predict attitude. These results suggest that perceived risk might reflect deeper structural concerns like system bias, data protection, or control imbalances, which solely trust cannot mitigate. It also may be indicative of the increasing normalisation of AI technologies among younger users or the sense of inevitability around

algorithmic screening. This confirms Araujo et al.'s (2020) argument that risk perceptions fluctuate across sectors and contexts.

On the other hand, the confirmed positive effect of transparency validates the FATE framework, which suggests that the more users understand the functionality of AI systems, the more they hold a positive attitude toward them. This positive effect of perceived transparency on candidates' attitudes towards AI-enabled recruitment is consistent with existing theory and empirical research. The result confirms Bedué and Fritzsche (2022) argument that perceived transparency is a core antecedent of trusting AI by helping users to have a meaningful understanding of how algorithmic decisions are being made. In this study, when candidates perceived the AI-enabled recruitment system as transparent, they formed positive attitudes, proving that explainability is a critical relational and functional role in shaping acceptance. Additionally, the result supports the findings of Felzmann et al. (2019), AbdulKareem et al. (2024), and Angerschmid et al. (2022), who underline that transparency—especially supplemented with context and communicated appropriately—provides users with more confidence when interacting with AI systems. The moderating role of AI experience aligns with AbdulKareem et al. (2024) observation that digital literacy strengthens the perception of transparency and the transparency–acceptability relationship.

Perceived fairness shown to significantly influence job candidates' attitudes toward AI-enabled recruitment, confirming the previous literature underlining fairness as a prominent determinant of user acceptance in high-stakes decision contexts.

This result supports Kim and Heo (2021) and Nørskov et al. (2019), who exhibited that even when AI systems are deemed fair, they critically shape users' convenience and engagement. Furthermore, it confirms Teodorescu et al. (2021) argument that socio-technical fairness requires context-aware of human-AI collaboration. The findings thus build on previous research by empirically demonstrating that fairness is not a mere secondary consideration but rather a fundamental antecedent of candidate acceptance, which is particularly relevant for developing labour markets where ethical legitimacy might be scrutinised more closely due to comparatively weaker institutional safeguards.

The mediation of trust between transparency and attitude validates that explainability and openness towards the AI are key trust-building means and profoundly ethical imperatives. Candidates hold more positive attitudes when they believe AI decisions are interpretable and comprehensible directly, and through increased trust. However, the trust did not mediate the perceived risk–attitude relationship, implying a more complex pathway. Risk appeared to have a direct negative influence on attitudes, yet there was no significant intervention for trust in this relationship. These findings may indicate that candidates' risk perceptions stem from structural concerns and systemic issues, such as data misuse or bias that cannot be overcome by solely trusting the system's competence. Previous literature (Araujo et al., 2020; Li, 2025) has also found that high-risk contexts dictate more than trust to overcome user scepticism.

Respondents' prior AI experience moderated the relationship between perceived transparency and perceived risk with their attitude toward AI-enabled recruitment. The positive influence of transparency on attitude was stronger among those with more experience interacting with AI, which implies that experienced users are keener on the explanations and justifications behind the decisions. This finding aligns with the literature demonstrating how digital proficiency magnifies user expectations of clarity and fairness of AI (AbdulKareem et al., 2024; Shin, 2021).

Likewise, the adverse effect of risk on attitude was lessened for users with increased AI experience, suggesting that familiarity with AI lowers suspicion and increases AI acceptance. This finding has practical implications where increased awareness, familiarity, and training interventions might alleviate the risk perceptions, at least for less experienced candidates.

In contrast, AI experience did not moderate the effects of perceived fairness and ease of use on attitude, as these dimensions are arguably inherently salient qualities of the technology. Candidates could consider fair treatment and user-friendly systems as universally high priorities, even without

prior exposure to AI. These findings indicate that fairness is yet a first-order issue that cuts across technical competence.

The study helpfully addresses a broad gap in the literature by shifting focus from employer or system analysis toward candidate perceptions. It enriches conventional technology acceptance models by ingraining ethical and relational variables as core determinants of attitude and acceptance. Moreover, investigating the mediation role of trust strengthens its central role in aligning system features with user attitudes, which is a contribution to both AI trust and socio-technical literature.

The moderating role of experience adds a novel contextual layer. Furthermore, the nonsignificant influence of ease of use challenges traditional assumptions in TAM, suggesting that ethical concerns outweigh usability in evaluative contexts like recruitment.

Moreover, the outcomes support the calls for socio-technical models of AI acceptance (Glikson & Woolley, 2020; Wanner et al., 2022) that embrace the need to balance psychological, ethical, and contextual factors with technological efficiency. Trust, as proved here, is not an inherent characteristic but a function framed by the system characteristics and users' familiarity and experience.

The findings emphasise the importance of AI transparency and fairness for HR professionals and technology developers. Perception of fairness and decision-making clarity are vital to users' acceptance and trust. Organisations must embrace explainable AI interfaces and formulate exhaustive policies to ensure procedural fairness. The findings underscore the importance of educating candidates about AI tools and enforcing familiarity within the process. To build a sounder understanding of AI-enabled tools, increasing trust and lowering negative risk perceptions, digital orientation sessions or interactive explainers could be utilised to give inexperienced applicants.

Since attitude and trust are found to be strongly correlated, hiring processes should include trust-building strategies, such as human oversight, transparent scoring rubrics, or ethical assurances. Not only do these actions enhance acceptance, but they also promote organisational legitimacy and reputation.

Conclusions

This study contributes to understanding AI-enabled recruitment acceptance from job candidates' perspectives in an emerging market context, such as Jordan. Specifically, it investigates the role of their fairness, transparency, risk, trust, usefulness, and ease of use perceptions while considering their prior AI experience as a moderator. Grounded on preceding technology adoption (TAM, UTAUT, and the FATE framework) as a theoretical foundation, the study incorporated essential ethical and psychological dimensions into a candidate-centric framework by integrating context-specific ethical and experiential dimensions relevant to the HR recruitment context. The findings offer theoretical insights and practical implications for the responsible and inclusive usage of AI in processing hiring decisions.

The findings revealed that AI trust, perceived fairness, usefulness, and transparency significantly affect shaping candidate attitudes toward AI-enabled recruitment. On the other hand, ease of use and risk perception had no substantial direct effect, implying that respondents placed greater importance on AI ethical and relational characteristics over technical functionality.

Additionally, the significant mediation role of trust between fairness, transparency, and attitude confirms its role as a bridge between ethical system characteristics and acceptance. The moderating role of AI-experience on the effects of transparency and risk emphasises the importance of familiarity in shaping receptiveness to AI.

These findings underline the necessity of producing AI systems that are functionally efficient but also fair, transparent, and trustworthy. As AI continues to reshape HRM practices, organisations should not wait passively until AI video interviews are common practice; instead, proactively address user concerns in the early stages of such HRM implementations, especially among external users such as job applicants who have no direct control over or adequate awareness of the used algorithms.

By grounding these recommendations in the Jordanian context of high youth unemployment and low levels of trust among the public for automated decision-making, this study contributes to context-specific insights which is often missing in Western-centric AI research. It supports the goals of SDG 8 ("Decent Work and Economic Growth"), specifically target 8.5, which advocates for fair and inclusive hiring practices.

In conclusion, as AI transforms the way HRM work is done around the globe, organisations need to consider building trust, fairness, and transparency, especially when leveraging AI tools that connect external stakeholders such as job candidates. The study advocates that when it comes to AI and automation, moving away from a technologically deterministic approach toward developing human-centred, trust-aware frameworks to facilitate responsible AI adoption.

Although the study offers valuable input to the technology adoption and acceptance literature by investigating candidates' attitudes toward AI-enabled recruitment, several limitations must be acknowledged. Firstly, it is limited to the Jordanian pharmaceutical sector while targeting limited preselected job vacancies at entry to mid-level careers. As such, this industry-specific and regional frame may constrain the generalizability to other sectors, labour markets and cultures with distinctive technological infrastructure, job applicants' expectations, or social norms.

Additionally, employing a cross-sectional design that captures perceptions at a specific point in time does not consider the potential shifts in attitude during the recruitment process that might happen after repeated exposure to AI-enabled systems. Longitudinal studies are recommended as they yield an improved understanding of trust, resistance, and perceptions evolution through the employment process up to receiving the final employment decision.

Although self-reported data, such as questionnaire-based methods, are well-suited to measure perceptions, they may be prone to social desirability bias or limited knowledge of the underlying functionality. Future research that comprises experimental simulations, behavioural data, or system logs is recommended to triangulate how candidates react to algorithmic real-time decisions.

The study considered only a single moderating variable, respondents' experience with AI. Although it proved insightful, Further research might consider broadening the investigation to incorporate other potential moderators such as perceptions of justice in the organisation, personality traits, social pressure, digital literacy, and others.

Lastly, although attitude is argued to be the strongest predictor of acceptance and intention, this study did not examine the complete outcomes, such as respondents' continuation or withdrawal, organisational attractiveness, and recruitment process effectiveness. Future research that investigates the influence of perceptions on applicants' actual behaviour and decisions throughout and after the recruitment process.

Author Contributions: Conceptualisation, B.H., O.H.; methodology, B.H., O.H.; formal analysis: B.H., G.S.; validation: B.H., G.S.; data curation, B.H., G.S.; writing-review and editing, B.H., O.H.; writing-original draft preparation, B.H., O.H.; supervision, B.H. All authors have read and agreed to the published version of the manuscript.

Funding: The authors declare that no funding was received for the conduct of this research or the preparation of this article.

Data Availability Statement: The data supporting the findings of this study are available on request from the corresponding author.

Conflicts of Interest: The authors affirm no conflict of interest.

Reference

1. AbdulKareem, A. K., Oladimeji, K. A., Ishola, A. A., Bello, M. L., Umar, A. Y., & Adejumo, A. (2024). Investigating ICT adoption and public value of e-recruitment in the public sector: the role of social media use. *International Journal of Public Sector Management*, 37(2), 284–304. <https://doi.org/10.1108/IJPSM-10-2023-0307>.

2. Ali, I., Warraich, N. F., & Butt, K. (2025). Acceptance and use of artificial intelligence and AI-based applications in education: A meta-analysis and future direction. *Information Development*, 41(3), 859–874. <https://doi.org/10.1177/02666669241257206>.
3. Allal-Chérif, O., Aránega, A. Y., & Sánchez, R. C. (2021). Intelligent recruitment: How to identify, select, and retain talents from around the world using artificial intelligence. *Technological Forecasting and Social Change*, 169, Article 120822. <https://doi.org/10.1016/j.techfore.2021.120822>.
4. Angerschmid, A., Zhou, J., Theuermann, K., Chen, F., & Holzinger, A. (2022). Fairness and explanation in AI-informed decision making. *Machine Learning and Knowledge Extraction*, 4(2), 556–579. <https://doi.org/10.3390/make4020026>.
5. Araujo, T., Helberger, N., Kruikemeier, S., & De Vreese, C. H. (2020). In AI we trust? Perceptions about automated decision-making by artificial intelligence. *AI & society*, 35(3), 611–623. <https://doi.org/10.1007/s00146-019-00931-w>.
6. Bedué, P., & Fritzsche, A. (2022). Can we trust AI? An empirical investigation of trust requirements and guide to successful AI adoption. *Journal of Enterprise Information Management*, 35(2), 530–549. <https://doi.org/10.1108/JEIM-06-2020-0233>.
7. Binns, R. (2018, January). Fairness in machine learning: Lessons from political philosophy. In S. Venkatasubramanian, K. Fukumizu, C. Ling, & J. Z. Kolter (Eds.), *Proceedings of the 2018 Conference on Fairness, Accountability and Transparency* (pp. 149–159). PMLR. <https://dl.acm.org/doi/10.1145/3287560.3287598>.
8. Bringsjord, S. (2011). Psychometric artificial intelligence. *Journal of Experimental & Theoretical Artificial Intelligence*, 23(3), 271–277. <https://doi.org/10.1080/0952813X.2010.502314>.
9. Chaudhary, G. (2024). Unveiling the black box: Bringing algorithmic transparency to AI. *Masaryk University Journal of Law and Technology*, 18(1), 93–122. <https://doi.org/10.5817/MUJLT2024-1-4>.
10. Chin, W. W. (1998). Commentary: Issues and Opinion on Structural Equation Modeling. *MIS Quarterly*, 22(1), vii–xvi. <http://www.jstor.org/stable/249674>.
11. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, 319–340. <https://doi.org/10.2307/249008>.
12. Dastin, J. (2022). Amazon scraps secret AI recruiting tool that showed bias against women. In *Ethics of data and analytics* (pp. 296–299). Auerbach Publications.
13. Deepa, R., Sekar, S., Malik, A., Kumar, J., & Attri, R. (2024). Impact of AI-focussed technologies on social and technical competencies for HR managers—A systematic review and research agenda. *Technological Forecasting and Social Change*, 202, Article 123301. <https://doi.org/10.1016/j.techfore.2024.123301>.
14. De Visser, E. J., Pak, R., & Shaw, T. H. (2018). From ‘automation’ to ‘autonomy’: the importance of trust repair in human–machine interaction. *Ergonomics*, 61(10), 1409–1427. <https://doi.org/10.1080/00140139.2018.1457725>.
15. Felzmann, H., Villaronga, E. F., Lutz, C., & Tamò-Larrieux, A. (2019). Transparency you can trust: Transparency requirements for artificial intelligence between legal norms and contextual concerns. *Big Data & Society*, 6(1), Article 2053951719860542. <https://doi.org/10.1177/2053951719860542>.
16. Figueroa-Armijos, M., Clark, B. B., & da Motta Veiga, S. P. (2023). Ethical perceptions of AI in hiring and organizational trust: The role of performance expectancy and social influence. *Journal of Business Ethics*, 186(1), 179–197. <https://doi.org/10.1007/s10551-022-05166-2>.
17. Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research*, 18(1), 39–50. <https://doi.org/10.1177/002224378101800104>.

18. Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of management annals*, 14(2), 627–660. <https://doi.org/10.5465/annals.2018.0057>.
19. Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). Multivariate data analysis.
20. Haque, A. B., Islam, A. N., & Mikalef, P. (2023). Explainable Artificial Intelligence (XAI) from a user perspective: A synthesis of prior literature and problematizing avenues for future research. *Technological Forecasting and Social Change*, 186, Article 122120. <https://doi.org/10.1016/j.techfore.2022.122120>.
21. Herzallah, A. M., & Makaldy, R. (2025). Technological Self-Efficacy and Sense of Coherence: Key Drivers in Teachers' AI Acceptance and Adoption. *Computers and Education: Artificial Intelligence*, Article 100377. <https://doi.org/10.1016/j.caeai.2025.100377>.
22. Hilliard, A., Guenole, N., & Leutner, F. (2022). Robots are judging me: Perceived fairness of algorithmic recruitment tools. *Frontiers in Psychology*, 13, Article 940456. <https://doi.org/10.3389/fpsyg.2022.940456>.
23. Hofeditz, L., Clausen, S., Rieß, A., Mirbabaie, M., & Stieglitz, S. (2022). Applying XAI to an AI-based system for candidate management to mitigate bias and discrimination in hiring. *Electronic Markets*, 32(4), 2207–2233. <https://doi.org/10.1007/s12525-022-00600-9>.
24. Hu, J., Huang, G. I., Wong, I. A., & Wan, L. C. (2024). AI trust divide: How recruiter-candidate roles shape tourism personnel decision-making. *Annals of Tourism Research*, 109, Article 103860. <https://doi.org/10.1016/j.annals.2024.103860>.
25. Hunkenschroer, A. L., & Luetge, C. (2022). Ethics of AI-enabled recruiting and selection: A review and research agenda. *Journal of Business Ethics*, 178(4), 977–1007. <https://doi.org/10.1007/s10551-022-05049-6>.
26. Ibrahim, F., Münscher, J. C., Daseking, M., & Telle, N. T. (2025). The technology acceptance model and adopter type analysis in the context of artificial intelligence. *Frontiers in Artificial Intelligence*, 7, Article 1496518. <https://doi.org/10.3389/frai.2024.1496518>.
27. Ismatullaev, A., & Kim, S. (2022). Review of the factors affecting acceptance of AI-infused systems. *Human Factors*, 64(8), 1323–1340. <https://doi.org/10.1177/00187208211064707>.
28. Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business horizons*, 62(1), 15–25. <https://doi.org/10.1016/j.bushor.2018.08.004>.
29. Kelly, S., Kaye, S. A., & Oviedo-Trespalacios, O. (2023). What factors contribute to the acceptance of artificial intelligence? A systematic review. *Telematics and Informatics*, 77, Article 101925. <https://doi.org/10.1016/j.tele.2022.101925>.
30. Kim, J. Y., & Heo, W. (2021). Artificial intelligence video interviewing for employment: perspectives from applicants, companies, developer and academicians. *Information Technology & People*, 35(3), 861–878. <https://doi.org/10.1108/ITP-04-2019-0173>.
31. Langer, M., König, C. J., & Papathanasiou, M. (2021). Highly automated job interviews: Acceptance under the influence of stakes and performance feedback. *Journal of Business and Psychology*, 36, 707–726. <https://doi.org/10.1111/ijbsa.12246>.
32. Larsson, S., White, J. M., & Ingram Bogusz, C. (2024). The Artificial Recruiter: Risks of Discrimination in Employers' Use of AI and Automated Decision-Making. *Social Inclusion*, 12. <https://doi.org/10.17645/si.7471>.
33. Lashkari, M., & Cheng, J. (2023, April). “Finding the Magic Sauce”: Exploring Perspectives of Recruiters and Job Seekers on Recruitment Bias and Automated Tools. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems* (pp. 1-16). <https://doi.org/10.1145/3544548.3581548>.
34. Lee, M. K. (2018). Understanding perception of algorithmic decisions: Fairness, trust, and emotion in response to algorithmic management. *Big data & society*, 5(1), Article 2053951718756684. <https://doi.org/10.1177/2053951718756684>.

35. Lee, M. K., Jain, A., Cha, H. J., Ojha, S., & Kusbit, D. (2019). Procedural justice in algorithmic fairness: Leveraging transparency and outcome control for fair algorithmic mediation. *Proceedings of the ACM on Human-Computer Interaction*, 3(CSCW), 1–26. <https://doi.org/10.1145/3359284>.
36. Li, W. (2025). A study on factors influencing designers' behavioral intention in using AI-generated content for assisted design: Perceived anxiety, perceived risk, and UTAUT. *International Journal of Human-Computer Interaction*, 41(2), 1064–1077. <https://doi.org/10.1080/10447318.2024.2310354>.
37. Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of organizational trust. *Academy of management review*, 20(3), 709–734. <https://doi.org/10.5465/amr.1995.9508080335>.
38. McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). Developing and validating trust measures for e-commerce: An integrative typology. *Information systems research*, 13(3), 334–359. <https://doi.org/10.1287/isre.13.3.334.81>.
39. McLean, G., Osei-Frimpong, K., Wilson, A., & Pitardi, V. (2020). How live chat assistants drive travel consumers' attitudes, trust and purchase intentions: the role of human touch. *International Journal of Contemporary Hospitality Management*, 32(5), 1795–1812. <https://doi.org/10.1108/IJCHM-07-2019-0605>.
40. Moravec, V., Hynek, N., Gavurova, B., & Kubak, M. (2024). Everyday artificial intelligence unveiled: Societal awareness of technological transformation. *Oeconomia Copernicana*, 15(2), 367–406. <https://doi.org/10.24136/oc.2961>.
41. Mirowska, A., & Mesnet, L. (2022). Preferring the devil you know: Potential applicant reactions to artificial intelligence evaluation of interviews. *Human Resource Management Journal*, 32(2), 364–383. <https://doi.org/10.1111/1748-8583.12393>.
42. Nørskov, S., Damholdt, M. F., Ulhøi, J. P., Jensen, M. B., Mathiasen, M. K., Ess, C. M., & Seibt, J. (2019, July 4–6). Fairness perceptions in job interviews: Using a teleoperated robot as a fair proxy. *Paper presented at the 35th European Group for Organizational Studies (EGOS) Colloquium, University of Edinburgh Business School, Edinburgh, United Kingdom*. <https://pure.au.dk/portal/en/publications/fairness-perceptions-in-job-interviews-using-a-teleoperated-robot/>
43. Ochmann, J., & Laumer, S. (2019). Fairness as a determinant of AI adoption in recruiting: An interview-based study.
44. Ochmann, J., Michels, L., Tiefenbeck, V., Maier, C., & Laumer, S. (2024). Perceived algorithmic fairness: An empirical study of transparency and anthropomorphism in algorithmic recruiting. *Information Systems Journal*, 34(2), 384–414. <https://doi.org/10.1111/isj.12482>.
45. Ogunniye, G., Legastelois, B., Rovatsos, M., Dowthwaite, L., Portillo, V., Vallejos, E. P., & Jirotko, M. (2021). Understanding user perceptions of trustworthiness in e-recruitment systems. *IEEE Internet Computing*, 25(6), 23–32. <http://doi.org/10.1109/MIC.2021.3115670>.
46. Omohundro, S. (2014). Autonomous technology and the greater human good. *Journal of Experimental & Theoretical Artificial Intelligence*, 26(3), 303–315. <https://doi.org/10.1080/0952813X.2014.895111>.
47. Ore, O., & Sposato, M. (2022). Opportunities and risks of artificial intelligence in recruitment and selection. *International Journal of Organizational Analysis*, 30(6), 1771–1782. <https://doi.org/10.1108/IJOA-07-2020-2291>.
48. Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. *International journal of electronic commerce*, 7(3), 101–134. <https://doi.org/10.1080/10864415.2003.11044275>.
49. Prikshat, V., Kumar, S., Patel, P., & Varma, A. (2025). Impact of organisational facilitators and perceived HR effectiveness on acceptance of AI-augmented HRM: an integrated TAM and TPB perspective. *Personnel Review*, 54(3), 879–912. <https://doi.org/10.1108/PR-04-2023-0303>.

50. Qutaishat, F., Abushakra, A., Anaya, L., & Al-Omari, M. (2023). Investigating the factors affecting the intention to adopt cloud-based ERP systems during the COVID-19 era: evidence from Jordan. *Business Process Management Journal*, 29(3), 653–670. <https://doi.org/10.1108/BPMJ-09-2022-0462>.
51. Rigotti, C., & Fosch-Villaronga, E. (2024). Fairness, AI & recruitment. *Computer Law & Security Review*, 53, Article 105966. <https://doi.org/10.1016/j.clsr.2024.105966>.
52. Robert, L. P., Pierce, C., Marquis, L., Kim, S., & Alahmad, R. (2020). Designing fair AI for managing employees in organizations: a review, critique, and design agenda. *Human–Computer Interaction*, 35(5-6), 545–575. <https://doi.org/10.1080/07370024.2020.1735391>.
53. Rukadikar, A., & Khandelwal, K. (2024). Navigating change: a qualitative exploration of chatbot adoption in recruitment. *Cogent Business & Management*, 11(1), Article 2345759. <https://doi.org/10.1080/23311975.2024.2345759>.
54. Sekaran, U., & Bougie, R. (2016). Research methods for business: A skill building approach. John Wiley & Sons.
55. Sheng, H., Nah, F. F.-H., & Siau, K. (2008). An experimental study on ubiquitous commerce adoption: Impact of personalization and privacy concerns. *Journal of the Association for Information Systems*, 9(6), 367–391. <https://doi.org/10.17705/1jais.00161>.
56. Shin, D. (2020). User perceptions of algorithmic decisions in the personalized AI system: Perceptual evaluation of fairness, accountability, transparency, and explainability. *Journal of Broadcasting & Electronic Media*, 64(4), 541–565. <https://doi.org/10.1080/08838151.2020.1843357>.
57. Shin, D. (2021). Shin, D. (2021). Shin, D. (2023). Embodying algorithms, enactive artificial intelligence and the extended cognition: You can see as much as you know about algorithm. *Journal of Information Science*, 49(1), 18–31. <https://doi.org/10.1177/0165551520985495>.
58. Straub, D. W. (1989). Validating instruments in MIS research. *MIS quarterly*, 13(2), 147–169. <https://doi.org/10.2307/248922>.
59. Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial intelligence in human resources management: Challenges and a path forward. *California Management Review*, 61(4), 15-42. <https://doi.org/10.1177/0008125619867910>.
60. Tanantong, T., & Wongras, P. (2024). A UTAUT-based framework for analyzing users' intention to adopt artificial intelligence in human resource recruitment: a case study of Thailand. *Systems*, 12(1), 28. <https://doi.org/10.3390/systems12010028>.
61. Teodorescu, M. H., Morse, L., Awwad, Y., & Kane, G. C. (2021). Teodorescu, M. H., Morse, L., Awwad, Y., & Kane, G. C. (2021). Failures of fairness in automation require a deeper understanding of human–ml augmentation. *MIS quarterly*, 45(3), 1483–1500. <https://doi.org/10.25300/MISQ/2021/16535>.
62. United Nations. (2015). Our common future: Report of the World Commission on Environment and Development. Oxford: Oxford University Press.
63. Upadhyay, A. K., & Khandelwal, K. (2018). Applying artificial intelligence: implications for recruitment. *Strategic HR Review*, 17(5), 255–258. <https://doi.org/10.1108/SHR-07-2018-0051>.
64. Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management science*, 46(2), 186–204. <https://doi.org/10.1287/mnsc.46.2.186.11926>.
65. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly*, 27(3), 425–478. <https://doi.org/10.2307/30036540>.
66. Wang, R., Harper, F. M., & Zhu, H. (2020, April). Factors influencing perceived fairness in algorithmic decision-making: Algorithm outcomes, development procedures, and individual

- differences. In *Proceedings of the 2020 CHI conference on human factors in computing systems* (pp. 1-14). <https://doi.org/10.1145/3313831.337681>.
67. Wang, S. C. (2003). Artificial neural network. In *Interdisciplinary computing in java programming* (pp. 81-100). Boston, MA: Springer US.
 68. Wanner, J., Herm, L. V., Heinrich, K., & Janiesch, C. (2022). The effect of transparency and trust on intelligent system acceptance: Evidence from a user-based study. *Electronic Markets*, 32(4), 2079–2102. <https://doi.org/10.1007/s12525-022-00593-5>.
 69. Wongras, P., & Tanantong, T. (2023). An extended UTAUT model for analyzing users' Acceptance factors for artificial Intelligence adoption in human resource recruitment: A case study of Thailand. *Education and Information Technologies*, 3(7), 13–27. <http://doi.org/10.20944/preprints202311.1612.v1>.
 70. Xiong, Y., & Kim, J. K. (2025). Who wants to be hired by AI? How message frames and AI transparency impact individuals' attitudes and behaviors toward companies using AI in hiring. *Computers in Human Behavior: Artificial Humans*, 3, Article 100120. <https://doi.org/10.1016/j.chbah.2025.100120>.
 71. Zerilli, J., Bhatt, U., & Weller, A. (2022). How transparency modulates trust in artificial intelligence. *Patterns*, 3(4), Article 100455. <https://doi.org/10.1016/j.patter.2022.100455>.

Taste, Quality or Price? Investigating Consumer Patriotism in the Food Market

Julia Wojciechowska-Solis^{1*}, Aleksandra Kowalska²

¹ University of Life Sciences in Lublin, Poland
ORCID: 0000-0002-4634-0241
e-mail: julia.wojciechowska@up.lublin.pl

² Maria Curie-Skłodowska University, Poland
ORCID: 0000-0003-3854-951X
e-mail: aleksandra.kowalska@mail.umcs.pl

* Corresponding author: Julia Wojciechowska-Solis, julia.wojciechowska@up.lublin.pl

Abstract

Consumer patriotism is an important trend, alongside consumer trends such as prioritising health, caring for the environment and animal welfare. For many consumers, it is important to feel a direct linkage to the producer and to support the local economy through their purchase decisions concerning food. The purpose of this article was to deepen the understanding of consumer preferences on the local food market. The article fills a research gap in a thorough understanding of consumers' local food purchasing decisions which are based on economic considerations. Empirical research was conducted in March and April 2022 using the CAWI method. 1,009 questionnaires were analysed, with respondents from Poland stating that supporting the local economy is the main reason for purchasing local products. Descriptive statistics and the post hoc Dunn test with Kruskal–Wallis variance were used for the analyses. The results show that women are more likely to purchase local products. The purchase of these products is determined by "organoleptic qualities," the "opportunity to contact the producer directly," and "nutritional values." Dairy, bread, eggs, and groats are the most frequently chosen local foods. The vast majority of the surveyed sample is willing to accept a 10–15% premium on local products. Consumers of local products are often very loyal. This creates opportunities for the development of Internet sales. As ethnocentric consumers are more likely to buy regional food directly from the producer, facilitating the development of short supply chains and direct distribution by creating legislation that protects the consumer and the local producer/supplier is recommended.

Key words

consumer decisions, food market, willingness to purchase, consumer ethnocentrism, purchasing channels.

Cite as:

Wojciechowska-Solis, J., & Kowalska, A. (2025). Taste, Quality or Price? Investigating Consumer Patriotism in the Food Market. *Forum Scientiae Oeconomia*, 13(3), 114–130. https://doi.org/10.23762/FSO_V OL13_NO3_5

Received: 27 April 2025

Revised: 3 September 2025

Accepted: 25 September 2025



Copyright: © 2025 by the authors. For open-access publication within the terms and conditions of the Creative Commons Attribution (CC BY) licence (<https://creativecommons.org/licenses/by/4.0/>).

Introduction

Customers wishing to purchase goods or services nowadays face a huge dilemma. The multitude of products offered through different distribution channels, no longer on shop shelves alone but also via websites or television, often only adds difficulty to buyers struggling with the question of “what to buy?” With increasing globalisation, consumers can choose products from all over the world, browsing through various offers to buy goods without leaving their homes; thus, the increasingly common dilemma is no longer “what to buy?” but “where to buy from?” Nowadays, consumers tend to show signs of two polarised identities simultaneously: local and global (Bryła & Domański, 2023), although the availability of foreign goods and services raises doubts in some individuals as to whether purchasing goods produced outside of their country of residence is not in conflict with patriotic motives. The increasing length and complexity of food supply chains due to globalisation has caused

a reduction in links between producers and consumers, and reduced consumer confidence in purchased food. The development of local food markets provides an opportunity to create connections between consumers and producers and foster sustainable consumption behaviour on the food market (Weber et al., 2021). Local food systems, which emphasise sourcing food within a specific geographical area, have gained popularity together with the spread of ethnocentric attitudes, which have been related to the recent crises (the COVID-19 pandemic, the war in Ukraine and the climate crisis).

Consumer ethnocentrism originally manifested itself in agri-food products and has become more pronounced over time, especially in countries with high food self-sufficiency, including Poland (Kowalska et al., 2023). The attitudes and behaviours among Polish consumers in the food market are characterised by wide diversity (Nestorowicz et al., 2020). In recent years, consumers have paid growing attention to indigenous domestic food products, putting more trust in local producers. So far, no generally and globally accepted definition of local food has been developed. It is assumed that this term refers to food produced close to where it is consumed. What matters is the geographical distance or number of kilometres a product has to travel from the producer to the consumer (Wojcieszak-Zbierska, 2021). Lowering food miles generally means a smaller overall environmental footprint and more support for local economies and farmers. Despite their different meanings, the terms 'local' and 'regional' are widely overused and used interchangeably (Muça et al., 2021; Roy & Ballantine, 2020; Wojciechowska-Solis, 2022). Given the recognised lack of precision within norms, Roy (2022) customarily assumes that local foods are articles "produced in a non-industrial, non-mass manner, using local raw materials or local production methods, and targeting the local market" (including traditional, regional, and ecological products). Therefore, semantically, local products constitute a broader term than, for example, regional products.

Despite several studies investigating consumer ethnocentric attitudes and behaviour in the food market (Yonfá-Medranda et al., 2024), there is a gap in a thorough understanding of consumers' local food purchasing decisions which are based on economic considerations. Past studies have indicated that a consumer's sense of community, i.e. the emotional state of being part of a community, influences intention to buy local food (Russomanno & Tree, 2021; Suhartanto et al., 2024a; Zhao & Wise, 2019), whereas our study investigates consumer purchasing of local food motivated by a desire to support local businesses. To the best of the authors' knowledge, this is the first such study conducted in Central and Eastern Europe. The results of the research might be useful for public authorities and food business operators from other countries of Central and Eastern Europe to develop adequate policies and strategies regarding local food products, and also for other researchers from this macroregion.

This study aims to diagnose the purchasing decisions of Polish consumers of local/domestic/regional food products, which are based on economic considerations. The study is exploratory in nature.

The paper is organised as follows: the Introduction conceptualises the term "local food" and presents the rationale for the study; Section 1 provides a literature review and builds upon the current knowledge to guide the research design and analysis; Section 2 outlines the methodological approach; Section 3 presents the research findings; Section 4 discusses the results; and the final section, the Conclusions, offers the authors' final remarks and summarises the theoretical contributions, practical and managerial implications, limitations, and directions for future research.

1. Literature review

Consumer ethnocentrism is classically associated with shopping patriotism on a national scale; however, this phenomenon is often used on a regional scale by companies offering products locally to gain competitive advantage. Ethnocentrism means preferring products of indigenous origin and emphasising their positive features over imported products, as well as rejecting foreign products (Witek-Hajduk & Grudecka, 2022). Consumer ethnocentrism can be defined as a sense of

responsibility, loyalty, and morality of buyers of domestically produced products. Ethnocentric consumers tend to believe that buying local products is appropriate for economic (supporting local economic development, reducing unemployment rate), emotional (pride in one's products, national pride, affirmation of one's culture and its products, and depreciation of other cultures) and moral reasons (Skallerud & Wien, 2019). Our study is focusing on consumer purchasing behavior motivated by economic factors in relation to local food.

The role of ethnocentrism and the country-of-origin effect has been increasing over recent decades. The research shows that the level of consumer ethnocentrism in the food market in Poland is quite high compared to other European countries and the patriotic aspect leads them to prefer Polish products (Bryła & Diomański, 2023). The strength of consumer ethnocentrism depends, among others, on the country of residence/origin of the respondents. In developing countries, such as Turkey, it has been shown that consumers do not want to buy foreign products because it harms domestic economy and causes unemployment. Given a choice, the ethnocentric consumer always prefers domestic products over foreign products and is guided not only by rational (economic) considerations, but also emotional and moral ones (Balabanis & Siamagka, 2022; Migliore et al., 2021; Trivedi et al., 2024; Karoui & Khemakhem 2019; Čvirik & Dotong, 2024; Khavari et al., 2024; Nguyen et al., 2023; Smoluk-Sikorska et al., 2024). If a buyer pays attention to the place of production, the image of the region of production, as well as the customer's attitude towards that region, are of major importance when it comes to deciding whether to purchase the product. This is confirmed by the research among German consumers (sympathy to a given land was clearly reflected in the evaluation of foods originating from the region) (Gebhardt et al., 2020). It is still an open question whether it is not the case that the image of regional food products shapes the image of the region.

Many circumstances influence the formation of ethnocentric attitudes in society; however, progressing globalisation and increasing the role of the Internet and social media in communicating with the public and assisting consumers in making food choices are of particular importance. Moreover, buyers, tired of the monotony of the same global goods offered to them, are looking for niche products that stand out for their individuality, having distinguishing features that cannot be found anywhere else. The consumer, as an active actor on the market, is searching for identity, desiring to once again find the right place in his/her little homeland, especially feeling anonymous in a culture of globalisation, where hypermarkets, as the main seller, are offering the same food all over the world (Bodescu & Moraru, 2022) and the global fast-food market is growing steadily (Mukucha & Jaravaza, 2021). The consumer is looking for an alternative that would allow him/her to discover their individuality. Moreover, feeling unity with the local community allows the consumer to become a citizen of his/her 'little homeland' again and reinforces a sense of security. Purchasing regional products becomes, to some extent, a reflection of the individual's longing for tradition (Kamińska & Krakowiak-Drzewiecka, 2023).

When making local food purchasing decisions, consumers pay attention to nutritional value and healthiness, freshness, high quality, safety, animal welfare, environmental impact, support of the local economy, taste, price, availability, traceability, place of origin, convenience, reliability etc. (da Costa Marques et al. 2022; Kovács et al., 2022). Brozzi et al. (2016) has also shown that consumers' cultural background and spatial typology (urban, predominantly urban and rural place of residence) have a significant influence on their preferences for local food purchase. Given that local food category embrace traditional, regional, and environmentally friendly products (Roy, 2022), it is worth to have a closer look at factors motivating the purchase of organic food. Massey et al. (2018) classified the determinants driving organic food purchases by mapping them onto (1) credence attributes – comprising intrinsic factors such as health benefits, quality, safety, and nutritional content, and extrinsic factors including environmental impact, animal welfare, and production standards – alongside (2) search attributes, which involve price, availability, and appearance, and (3) experience attributes, defined by organoleptic properties. Organic foods are credence goods, as consumers cannot directly verify attributes such as livestock grazing access or stocking density and must

therefore rely on trust (Manning and Kowalska, 2021). Hence, we propose the following research question:

Q1. What factors determine the purchase of local/domestic/regional food by consumers living in cities, towns and villages?

Starting from the second half of the 1990s, the issue of ethnocentric attitudes has been the subject of research in Poland and other central European countries (Jadach, 2021; Řezanková et al., 2023; Szwed, 2018). Such consumer studies have been often related to the food market (Nolan & Hobbs, 2023; Szabuniewicz & Majkut, 2021; Kaczmarek & Wieja, 2021; Suhartanto et al., 2024b). It is a fact that consumer patriotism in Poland has been changing dynamically in the context of globalisation. In the 1990s, there was an “infatuation” with foreign products following Poland’s political and economic transformation. This resulted in the buyers being characterised more by consumer internationalism – a phenomenon opposite to consumer ethnocentrism – Poles slowly turned towards indigenous products (Drabik, 2022). Such a trend is also related to the outbreak of the COVID-19 pandemic and the deepening economic crisis (E.I.T. Food, 2020; Yu et al., 2022). Purchasing domestic goods is beginning to be perceived as an investment in the national economy, support for domestic production, prevention of local unemployment and a contribution to availability and stability of food supply which is crucial for ensuring food and nutrition security. In Poland, consumer ethnocentrism is usually associated with buying goods with the inscription made in Poland, although this phenomenon can also be observed locally or regionally (Angowski & Jarosz-Angowska, 2020). It can also include actions undertaken not only by consumers but also by other business operators who promote the development of domestic companies. In the case of consumers, it means that in all their market behaviours, especially when making choices and purchases of goods and services, they are guided mainly by the benefits for their country (Hanus, 2020).

Consumer’s orientation towards domestic products is reinforced by external factors such as campaigns and social pressure, the strength of consumption traditions, often brought from home, as well as food nostalgia (Han, 2023; Rytönen et al., 2024). This develops a certain level of economic awareness in the buyer, which affects all his/her consumer decisions in the future; it is a kind of responsibility, morality, and loyalty that induces the customer to purchase national goods out of concern for local prosperity. A characteristic feature of the Polish food market is the use of names of locations in the names of products so that consumers get a direct message about the place of production of a given item. Examples include Żywiec Zdrój water, Nałęczowianka water, Tymbark juices, Pudliszki, Łowicz or Piątek articles. A further part of the name provides information about the qualities of the region, placed on packaging and labels, e.g. “From the Green Lungs of Poland”. The message the buyers receive evokes positive associations and prompts them to purchase the goods. It should be noted that the level of ethnocentrism is influenced by market signals. The state cultivates ethnocentric attitudes through the implementation of campaigns designed to enhance consumers’ socio-economic awareness and encourage the support of local businesses by choosing their products (Miftari et al., 2021), such as: ‘Teraz Polska’ [Poland Now], ‘Agro Polska’ [Agro Poland], ‘Produkt Polski’ [Polish Product] and ‘Dobre, bo polskie’ [It’s good because it’s Polish]. Furthermore, the EU quality schemes for traditional specialties guaranteed have been developed in order to facilitate the producers of traditional agricultural products, including foodstuffs, to communicate the value-adding attributes of their products to consumers. The quality schemes include: (i) protected designations of origin (PDO) and protected geographical indications (PGI) for agricultural products, including foodstuffs; (ii) traditional specialties guaranteed (TSG) and optional quality terms (Regulation (EU) 2024/1143).

In political discourse, the advancement of local food systems is frequently characterized as a strategy to enhance the resilience of the overall food system, mitigate its environmental impact, and support rural development as well as social cohesion within communities (a sense of community). Exploring consumers’ dietary choices and food purchasing decisions are key for both public and private decision-makers to develop and implement effective policy measures and

strategies aimed at promoting local food systems (Stein & Santini, 2022). These measures include, inter alia, educational campaigns and information messages (e.g. information provided on food labels). Therefore, the following research questions were posed:

Q2. Which local/domestic/regional products are most often chosen by Polish consumers?

Q3. How does the ethnocentric consumer react to price changes?

Q4. Where do consumers of local products mostly shop?

2. Methodology

The research was conducted in March/April 2022. The sample was selected based on respondents' availability and voluntary willingness to participate in the survey ($n=1,237$). With some caution, it can be said that this large-scale survey was conducted on a representative nationwide sample of Polish consumers. The eligibility criterion for further analysis, including statistical calculations, was the consumer's declaration that the guiding motive for purchasing local products was the intention to support local businesses, i.e. indicating a reason for economic consumer ethnocentrism. The questionnaires of 228 respondents who indicated that their decisions to buy local products were not related to the economic motive of purchase ethnocentrism were eliminated from further analysis. Ultimately, 1,009 (81.57%) correctly completed survey questionnaires were qualified for analysis. Women made up 68.29% of the sample and men 31.71% of the number of respondents (Table 1). Participation in the survey was voluntary and fully anonymous. The first part of the questionnaire aimed to identify the values important to the Polish consumer of local products. The second part was developed to identify preferences, motives, barriers, and channels for purchasing local products. The third part included metric questions. In the prepared questionnaire, mainly nominal and ordinal, five- and seven-point rating scales were used. It was decided to opt for a Likert scale because it enables to perform mathematical calculations with the use of variables measured on an interval scale. The measuring scales were validated in accordance with applicable regulations. The vast majority of scales were of our authorship and the scale items were verified on a 5-point Likert scale. The computer-assisted web interview (CAWI) method was used to collect the material. In the study, the value of the Cronbach α -test was within the range 0.70–0.90, which showed that the scales had internal consistency and reliability. Statistical analysis was assisted by Statistica 13.3 PL software.

Table 1. Socio-demographic profile of the consumer of local products supporting the economic development of the local environment by gender.

Variable name		Gender			
		Female		Male	
		N = 689	[%]	N = 320	[%]
Age	18-24 years old	300	43.54	120	37.50
	25-40 years old	210	30.48	116	36.25
	41-55 years old	153	22.21	76	23.75
	56 years old and more	26	3.77	8	2.50
Place of residence	Large city	249	36.14	96	30.00
	Small town	108	15.67	48	15.00
	Village	332	48.19	176	55.00
Household size	1-person household (I live alone)	52	7.55	32	10.00
	2-person household	88	12.77	76	23.75
	3-person household	168	24.38	76	23.75
	4-person (and more) household	381	55.30	136	42.50
Perception of one's financial situation	Good (I can afford to buy what I want)	301	43.69	132	41.25
	Average (I am able to buy most of the things I would like to have)	364	52.83	184	57.50
	Bad (I have just enough money to satisfy my basic needs)	24	3.48	4	1.25

Source: Own elaboration.

Those for whom supporting the local economy is an important aspect when making purchasing decisions described their financial situation positively. More than 50% of respondents estimate their financial situation as average and more than 40% of respondents believe their financial position is

good. Consumers of local products are mostly people living in three or four-person households (Table 1).

Firstly, descriptive statistics were used to analyse and interpret the results of the surveys. Secondly, the Kruskal-Wallis significance test (with Dunn test) for more than 2 surveyed groups was used to check the significance of differences between the groups of respondents. The test is non-parametric and its use becomes necessary in settings where the dependent variable is ordinal, where the assumption of normality cannot hold. Calculations were performed using STATISTICA 13.3 PL.

The influence of demographic and social variables on consumers' ethnocentric behaviour has already been extensively studied when researchers focused on the importance of these variables when making purchasing decisions (Department of Statistics, Ramadania et. al., 2023; Czine et al., 2024; Helly et al., 2022; Gupta, 2024; Miguel et. al., 2023; Vuong & Khanh Giao, 2020), although many authors (Thomas et al., 2020; Capelli et al., 2017; Bhattacharya et al., 2023; Yonfá-Medranda et al., 2024; Karoui & Khemakhem 2019) have indicated that the effect of age, gender, and/or educational level on ethnocentric purchasing behaviour is insignificant. However, Akbarov (2022) showed the significant moderating effect of gender, marital status, and personal income on the relationship between consumer ethnocentrism and purchasing behaviour in Azerbaijan.

Based on the work of the aforementioned researchers, the authors of this study chose the place of residence of the respondents as a differentiating variable for ethnocentric behaviour.

To identify alternate channels used to purchase local products, a purchase duplication analysis was applied. The purchase duplication analysis was originally developed by Ehrenberg (1988). It was initially used to analyse the patterns of consumption of various brands. Later, this method was also applied to the analysis of shopping channels used interchangeably by consumers. Drawing upon the research literature on the methodology of purchase duplication analysis, the authors of this study employed this method to investigate the channels used to purchase local products for all consumers in general, without dividing customers into groups, as the methodology suggests.

3. Research results

Respondents were asked to rate selected associations that were most frequent in the pilot study that the authors conducted in the year preceding this study. They considered the importance of six selected factors that affect their purchasing decisions concerning local food. In this case, a 5-point Likert scale was used (1 – I absolutely disagree; 5 – I absolutely agree). Polish consumers placed the highest value on organoleptic characteristics of local food (Table 2) (Q1).

Table 2. Selected factors determining the purchase of local food products.

Factor	Mean	Rural area	Small town	Large city	p-value
Organoleptic qualities	3.83	2.00a	4.06b	2.91c	0.000*
Nutritional values	2.43	2.33a	3.20b	2.90c	0.194
Product quality	1.96	1.62a	3.63b	2.23c	0.000*
Origin	2.25	2.63a	1.67b	2.91c	0.056
Short shelf life	2.30	2.68a	2.20b	2.86a	0.219
Opportunity to contact the producer directly	2.54	3.49a	1.33b	3.19a	0.000*

Note: * level of significant difference at $p < 0.050$. Different superscripts indicate significantly different means following the Kruskal-Wallis post hoc Dunn test.

Source: Own elaboration.

There were significant differences regarding the strength of influence of three factors on food choices made by consumers living in rural areas, towns, and cities, i.e. organoleptic qualities, the quality of production, and the opportunity to contact the producer directly. Analysing the results, a similarity between the group of respondents living in large cities and rural areas can be seen, which may be a result of urbanisation trends in Poland in recent years, where migrations of people of working age from large cities to rural and suburban areas have been noticeable. The “opportunity to contact the producer directly” is more important for these groups of respondents than for

respondents living in small towns. Such attributes of food products as “organoleptic qualities” and the “quality of production” are more important for the consumers from the group of “residents of small towns” than for the other two groups when deciding to purchase local foods (Q1).

Locally sourced products can be distinguished by various certification categories found on the product label. These include European Union certificates confirming the geographical origin of the product (PDO, PGI, GTS), national certificates („Jakość-Tradycja”, Agro Polska, Teraz Polska), certificates promoting local products (“Produkt Polski” Integrated Production, QMP, QAFP, GMO-Free), and certificates confirming that they are produced using environmentally friendly methods (organic food, Rainforest Alliance etc.).

Table 3 presents the preferences of the surveyed consumer groups related to the purchase of local foods from the eleven selected product groups. The preferences of the three consumer groups surveyed were significantly different only in the case of five product categories (dairy, eggs, sweets, meat and meat preparations) (Q2). A similarity can be again observed between respondents living in large cities and rural areas. They gave significantly higher ratings to such products as dairy, eggs, oil, and sweets. Only for the variable “meat and meat preparations”, despite the highest score of 3.84, does the group of respondents from large cities stand out significantly from the other two groups surveyed. This may prove that the consumers in large cities have greater access to a variety of products sold at various points of sale, i.e. large-format stores, speciality shops, island stands in shopping centres, or fairs held during festive periods. Thus, they have the opportunity to conveniently purchase and assess the qualities of local or regional products. Residents of rural areas mostly have direct contacts with the producers “from the neighbourhood”. Finally, Polish consumers in small towns often have limited physical access to local/regional foods due to the small number of points where these products are sold, which may have translated into lower scores in some categories. It's also worth mentioning that some local products are produced organically (such as vegetables and fruit, dairy, meat, and related products). This means they are often sold under the organic category in organic food stores, which are usually located in large cities.

Table 3. Purchasing preferences for selected local/regional/domestic products.

Selected local products	Place of residence			p-value
	Rural area	Small town	Large city	
Dairy	4.05a	4.59b	4.09a	0.016*
Fresh fruit and vegetables	3.43a	3.75b	4.03c	0.427
Bread	3.63a	3.79b	4.04a	0.928
Eggs	4.08a	3.64b	4.01a	0.023*
Groats	4.02a	4.50b	4.08a	0.067
Confectionery and biscuits	3.28a	3.27a	3.29a	0.992
Wine from a local vineyard	3.71a	3.14b	3.12b	0.281
Craft beer	3.47a	3.71b	3.42a	0.919
Oil	3.72a	2.93b	3.74a	0.038*
Sweets	3.68a	2.71b	3.84a	0.021*
Meat and meat preparations	3.45a	3.60a	3.84b	0.012*

Note: * level of significant difference at $p < 0.050$. Different superscripts indicate significantly different means following the Kruskal-Wallis post hoc Dunn test.

Source: Own elaboration.

Consumers of local products are often very loyal to specific producers and have a strong motivation to purchase chosen products, even if their prices increase (Q3). Financial situation, strong motivation, and other considerations allow more than 67% of respondents to maintain the same consumption level with an increase in the price of up to 15% (Table 4). With the price increase up to 25% more than ¼ of respondents (29.9%) are willing to keep their consumption of local products at the same level. A few percent of respondents say they will increase the quantity/frequency of local food purchases in such a situation. Unfortunately, around half of the respondents from each surveyed group declare that the increase in the price of local food by ¼ could result in a decrease in the quantity and/or frequency of purchases of these products. Around 20% of residents of rural areas and large

cities and just under 30% of residents of small towns say they would reduce their purchases of local food or look for cheaper mass-produced substitutes with a 10-15% price change. More than half of all respondents surveyed claimed they would decrease the quantity and frequency of local food purchases if their prices increased by 25% or more (Table 4). Large income disparities in Polish society between residents of large cities and small towns can still be observed. Residents of rural areas are often bi-vocational (they make their living not only by farming but additionally by working full-time) or they live in the countryside but commute to the city for work, and their income is higher than that of the average resident of a small town. Furthermore, the ongoing suburbanization process in Poland has facilitated shopping directly from the farmer for three decades (Kowalska, 2011).

Table 4. Consumer behaviour on the local food market in the event of a price change.

Change in product price		Place of residence						In total	
		Village		Small town		Large city			
		N = 508	[%]	N = 156	[%]	N = 345	[%]	1009	100%
Increase in price of local products by 25% or more	The quantity/frequency of purchases will remain the same	181	35.63	48	30.77	73	21.16	302	29.93
	I will increase the quantity/frequency of purchases	20	3.94	0	0.00	20	5.80	40	3.96
	I will decrease the quantity/frequency of purchases	246	48.43	80	51.28	200	57.97	526	52.13
	I will buy cheaper products of other origin if there is a change	61	12.01	28	17.95	52	15.07	141	13.98
Increase in price of local products by 10–15%	The quantity/frequency of purchases will remain the same	354	69.69	108	69.23	217	62.90	679	67.29
	I will increase the quantity/frequency of purchases	41	8.07	0	0.00	36	10.43	77	7.63
	I will decrease the quantity/frequency of purchases	101	19.88	44	28.21	80	23.19	225	22.30
	I will buy cheaper products of other origin if there is a change	12	2.36	4	2.56	12	3.48	28	2.78

Source: Own elaboration.

The research has shown that ethnocentric consumers who want to support the local economy prefer various channels for buying local foods (Table 5). Indeed, residents of large cities and those living in rural areas have a greater preference for discount and hypermarket shopping. Even though the opportunity to contact the producer directly is not a very important factor influencing the decision to buy local foods for the residents of small towns compared to other surveyed groups (Table 2), they prefer to buy local food directly from the farmer or local processor. This may be so because they particularly value the opportunity to obtain detailed information on production conditions or product characteristics by having direct contact with the producer. Shopping in speciality shops also has significantly more supporters among residents of small towns (Table 5) (Q4).

Table 5. Preferred channels for purchasing local food.

Factor	Mean	Rural area	Small town	Large city	p-value
Direct purchase from the producer (farmer/processor)	3.83	2.00a	4.06b	2.91c	0.000*
Purchase by You-Pick system (from the farmer's field/orchard)	2.43	2.33a	3.20b	2.90c	0.194
Purchase from a speciality shop	1.96	1.62a	3.63b	2.23c	0.000*
Purchase at a marketplace	2.25	2.63a	1.67b	2.91a	0.056
Online shopping – manufacturer's website	2.30	2.68a	2.20b	2.86a	0.219
Shopping during events, study tours	2.54	3.49a	1.33b	3.19a	0.000*
Discount shopping	3.27	4.03a	2.13b	3.92a	0.000*
Shopping in a hypermarket	3.00	3.85a	1.13b	3.79a	0.000*

Note: * level of significant difference at $p < 0.050$. Different superscripts indicate significantly different means following the Kruskal-Wallis post hoc Dunn test.

Source: Own elaboration.

The ability to substitute food distribution channels is very important when buying local products for consumers with ethnocentric beliefs. In the event of a product shortage, rather than look for a substitute, they search for alternate distribution channels. Table 6 shows consumer decisions concerning the substitutability of distribution channels for local food products (Q4).

Table 6. Selected duplication channels to already existing distribution channels for local food products.

Purchase Channel	Total	(A)	(B)	(C)	(D)	(E)	(F)	(G)
Directly from the producer (A)	54.5%	-	20.5%	5.5%	1.4%	9.6%	19.2%	20.5%
From a local wholesaler (B)	19.4%	57.7%	-	11.5%	7.7%	11.5%	19.2%	7.7%
General grocery stores (C)	3.7%	80.0%	60.0%	-	20.0%	40.0%	80.0%	20.0%
Supermarkets (D)	2.2%	33.3%	66.7%	33.3%	-	33.3%	33.3%	0.0%
Online purchasing (E)	6.0%	87.5%	37.5%	25.0%	12.5%	-	62.5%	50.0%
Speciality shops (F)	11.9%	87.5%	31.3%	25.0%	6.3%	31.3%	-	31.3%
Other (G)	21.6%	51.7%	6.9%	3.4%	0.0%	13.8%	17.2%	-
Average Duplication		66.28%	40.48%	19.64%	9.30%	25.98%	42.44%	21.80%

Note: Respondents could identify at least 3 alternate purchasing channels.

Source: Own elaboration.

Buying directly from the producer is the first choice for more than 54% of respondents. Only a few per cent of respondents buy local products from general grocery stores, supermarkets, or online. The data in the (A)-(G) columns of Table 6 show the percentage of consumers choosing one shopping channel, who use other channels at the same time. For example, almost 58% of consumers using channel B (buying from a local wholesaler) buy local food through channel A (directly from the producer). Furthermore, 80% of consumers who declare a preference for buying in general grocery stores (C) also buy products directly from producers (A) and the same percentage of consumers also buy local food in speciality shops (F). Despite the increasing popularity of the online purchasing channel, this channel was pointed out by only 6% of respondents as the main channel for purchasing local foods. Online shoppers (E) also choose either channel A (87.5%) or channel F (50%) as a substitute for their preferred place of purchase. Other purchasing channels not included in the table, e.g. roadside trade, sales at marketplaces and bazaars, sales at local events, and others, have been grouped under the term “other” (G). The survey has shown that channel G plays a relatively important role in the market. Customers predominantly using channel G usually choose channel A (direct purchase from the producer) as an alternative. The willingness to purchase local products during dedicated events (e.g. raspberry, buckwheat, or harvest festivals) and study tours (organised thematic trips) was declared by a large majority of the respondents (ca. 70%). It seems that consumers of local products are well-informed, know the offer, and use all possible purchasing channels.

Also noteworthy is that the Internet as a popular shopping channel in many markets does not work well among consumers of local products. The specificity of local products may also be related to the fact that consumers prefer direct contact with the producer (Table 6). Our respondents indicated the economic motive of ethnocentrism as the primary reason for local purchases. This may be the reason why it is more popular to buy directly from the producer, either from local company stores, trading next to a production plant, or selling points next to farm processing plants. What the consumer of local food probably appreciates about the supply chain is that it is short – the produce is fresh and the consumer is able to trace at least part of the journey from “farm to fork”. Furthermore, he/she might be aware of the impact of food choices on reducing food miles and carbon footprint.

4. Discussion

The study was to deepen the current understanding of the preferences of people who consider themselves patriots of domestic production, indicating that the basis of their decision is a conscious objective to support the local economy and improve the domestic labour market. The age of the average Polish consumer who cares about protecting the local market and appreciates the qualities of

local products has been decreased over the past few years. Earlier, Awdziej et al. (2016) in their study showed that it is the elderly who appreciate local products more, which may be linked to their income level and the level of knowledge about these products, but now Śliwa (2022) has shown that young people and women show greater consumer ethnocentrism and the least attention to the country of origin of the product is paid by people over 60 years of age. Similar findings are presented in our survey (Table 1).

The producer is intrinsically linked to the local product, often cultivating a family or local tradition, pursuing a passion, but mainly gaining a source of additional income. The research by da Costa Marques et al. (2022) and Van Bussel et al. (2022) confirmed the importance of such attributes of local products to the consumer as availability, support for the local economy, taste, place of origin, and producer recognition, and we came to similar results in our study (Table 2).

A systematic literature review conducted by Newman et al. (2014) showed that consumers in developed countries are often willing to pay more for domestic food products than others (convergence with the results of the study presented in Table 4). It is worth adding that according to experts from Polish economic portals, 9 out of 10 Polish consumers declare that the place of origin of food matters to them, while 59% of consumers are more likely to buy domestic products rather than imported ones (Forsal.pl, 2021). This creates opportunities for the growth of local/domestic/regional food markets and the development of less popular sales channels, like Internet sales. Our study shows that Polish consumers utilize a variety of channels to buy local foods, however, online purchasing channel is rarely chosen (Table 5 and 6). Providing wider access to these products should positively affect the development of disadvantaged regions. The development of infrastructure and technological security measures should contribute to the growing importance of online sales in the local food market.

According to Camacho et al. (2021), economic crises result in manifestations of consumer ethnocentrism, where the main reason for this manifestation is an economic motive. Akkaya (2021) drew a similar conclusion when surveying Turkish consumers. His study showed that Turkish consumers did not like to buy foreign products because it was harmful to the economy and caused unemployment, which is in line with the opinion of our respondents. In this regard, our study initially focused exclusively on the responses of consumers whose purchasing decisions in the food market were primarily driven by economic motives. Other motivations for purchasing local food will be examined in future research.

Not only Poles and other Europeans prefer to buy what is local; consumers from various countries located on continents such as Australia, South America (Chile) (Bianchi & Mortimer, 2015), North America (e.g. the United States), or Asia (China) (Zhang et al., 2020) are showing an increasing interest in local food, as well. Consumers consciously choose local products, paying attention to their organoleptic qualities and nutritional values, as well as to the opportunity to get to know the producer directly (sometimes even the whole history of the place/family that produces the local product offered). Local brands are becoming synonymous with high quality, freshness, safe ingredients, and simple and traditional recipes (PMR 2019). Such values were also indicated by consumers in the survey presented (Table 2). Similar conclusions were made by Sampalean et al. (2021), who highlighted that Italian consumers are also guided by selfish motives when buying traditional products, paying particular attention to the place of origin. A manifestation of patriotic motives is consumer ethnocentrism, which involves supporting local entrepreneurs, ensuring fair wages, and recognizing producers (Birch et al., 2018).

Consumer patriotism is an important trend, alongside consumer trends such as prioritising health, caring for the environment and animal welfare, or paying particular attention to the symbolism of a product, which is becoming increasingly important compared to classical competitive criteria (price, quality, availability) (Karoui & Khemakhem, 2019). These values are also respected when producing local food in organic production system. According to the study by Thøgersen (2023), consumers generally prefer domestic food products to imported ones and when choosing among domestic

products they mostly prefer local products. In his opinion, information about the locality of a product influences the purchase decision more than information that the product is organic. In recent years, the “You-Pick” system has become increasingly popular in horticultural holdings (Table 5). The willingness to purchase local products during dedicated events and study tours was declared by a majority of the respondents, which is in line with other studies (Dąbrowska, 2018; Maksan et al., 2019; Roy & Ballantine, 2020).

According to the PMR report (2019), for one in three people surveyed in Poland, consumer ethnocentrism is so important that consumers declare buying local products even if their prices increase. In the era of the coronavirus epidemic, economic uncertainty related to changes in global markets, and climate change, ethnocentric attitudes and behaviours are also a form of supporting local entrepreneurs. Consumers seeing the plight of small local entrepreneurs were more likely to opt for their offer, even though it was expensive. More than 60% of respondents to this survey indicated a 10-15% price change boundary, where they remain loyal to local products despite the price increase (Table 4.).

The fact that consumers use local origin as an indication of product quality was confirmed by Merle et al. (2016), who found that French consumers perceive local cheeses and apples to be healthier, tastier, and more environmentally friendly (Table 2 and 3). These consumers regarded their choices as the way to support French farmers. Similarly, the vast majority of participants in a representative survey of Polish consumers conducted by Bryła (2015) believed that local and regional food products were of higher quality than mass-produced food, as well as more trustworthy and authentic. Consumers view information about the origin of food products as an indication of a better taste experience (Maesano et al., 2020; Newman et al., 2014), which makes the decision-making process very complex and difficult to understand. The majority of consumers in Poland, New Zealand, the USA, or Italy, believe that local food products are healthier, fresher, tastier, higher quality, and more environmentally friendly than products from global brands (Bryła, 2019) (Table 2.).

Conclusions

This study, based on panel data from 38 OECD countries over the period 1995–2022, demonstrates that urbanization significantly moderates how economic complexity and capital formation influence environmental outcomes. Rather than serving as a passive backdrop, urban contexts actively condition both the direction and magnitude of these structural impacts on ecosystem vitality.

Three key findings emerge. First, the positive environmental contributions of economic complexity weaken as urban density increases. This attenuation likely reflects challenges such as congestion, resource competition, and diminishing returns to innovation in highly urbanized settings. Second, urbanization appears to mitigate the ecological costs associated with capital accumulation, likely through more efficient infrastructure use, shared systems, and stronger regulatory oversight. Third, the analysis confirms a nonlinear (inverted U-shaped) relationship between urbanization and environmental performance, consistent with the Urban Environmental Kuznets Curve hypothesis. Environmental degradation initially intensifies during early stages of urban growth but tends to improve once cities reach more advanced levels of development, likely due to enhanced governance capacities and greater diffusion of green technologies. This finding underscores the importance of urban governance capacity and integrated planning in achieving environmental sustainability, as emphasized by global frameworks (UN-Habitat, 2023).

The findings concerning energy dynamics reveal additional nuances. While renewable energy adoption consistently improves environmental quality, persistently high energy intensity continues to pose significant challenges. This suggests that while transitioning to renewable energy is essential, complementary strategies, such as implementing energy efficiency standards and promoting circular economy practices, are also critical for reducing overall energy demand and achieving deeper environmental gains.

From a policy perspective, these insights underscore the importance of spatially differentiated approaches. Efforts to promote economic complexity could be more effective when tailored to peri-urban or moderately dense areas, whereas capital investment strategies may benefit from focusing on compact, resource-efficient urban forms. Rather than viewing urbanization as uniformly beneficial or detrimental, policymakers are encouraged to recognize its contingent effects and design sustainability strategies that are sensitive to local urban contexts.

Theoretically, this study contributes to the ecological modernization literature by reframing urbanization as a moderating mechanism rather than an independent driver of environmental change. It also reinforces the Urban Environmental Kuznets Curve (UEKC) hypothesis by showing that sustainability outcomes hinge not only on affluence, but also on institutional maturity and technological absorption. Practically, the findings highlight the need for differentiated sustainability strategies that align with urban form, economic complexity, and capital dynamics.

Nonetheless, several limitations should be acknowledged. First, this study relies on country-level panel data, which may obscure important intra-national differences in urban structure and environmental governance. Second, while the analysis incorporates key structural and energy-related variables, it does not account for potentially influential institutional or cultural factors. Third, the exclusive focus on OECD countries may limit the generalizability of the findings to non-OECD or developing contexts.

Future research could further explore whether these moderating dynamics vary across (1) different regional groupings, (2) stages of economic development, or (3) urban governance models. Additionally, city-level analyses could offer more granular insights into how intra-urban variations shape the links between economic structure, urbanization, and environmental outcomes. City-level evidence further supports the dynamic relationship between urban growth and air quality (Zhu et al., 2025), highlighting the relevance of localized analyses in urban environmental studies. By conceptualizing urbanization as an active moderating force, this study offers a more sophisticated interpretation of how economic and ecological systems interact during sustainability transitions.

Author Contributions: Conceptualization, J.W-S. and A.K.; methodology, J.W-S. and A.K. software, J.W-S. and A.K; validation, J.W-S. and A.K.; formal analysis, J.W-S. and A.K.; investigation, J.W-S.; resources, J.W-S. and A.K; data curation, J.W-S. and A.K.; writing-original draft preparation, J.W-S. and A.K.; writing-review and editing, J.W-S. and A.K; visualization, J.W-S. and A.K.; supervision, J.W-S. and A.K.; project administration, J.W-S. and A.K. All authors have read and agreed to the published version of the manuscript.

Funding: This study was funded by the Lublin Universities Association (Związek Uczelni Lubelskich) under the "Staż za Miedzą" Program.

Data Availability Statement: The data that support the findings of this study are available from the author upon reasonable request.

Conflicts of Interest: The authors affirm no conflict of interest. The funders had no involvement in the study's design, data collection, analysis, manuscript writing, or the decision to publish the results.

Reference

1. Akbarov, S. (2022). Consumer ethnocentrism and purchasing behavior: moderating effect of demographics. *Journal of Islamic Marketing*, 13(4), 898–932. <https://doi.org/10.1108/jima-02-2020-0047>.
2. Akkaya, M. (2021). Understanding the impacts of lifestyle segmentation & perceived value on brand purchase intention: An empirical study in different product categories. *European Research on Management and Business Economics*, 27(3), Article 100155. <https://doi.org/10.1016/j.iedeen.2021.100155>.

3. Angowski, M., & Jarosz-Angowska, A. (2020). Importance of regional and traditional EU quality schemes in young consumer food purchasing decisions. *European Research Studies*, 23(2), 916–927. <https://doi.org/10.35808/ersj/1906>.
4. Awdziej, M., Tkaczyk, J., & Włodarek, D. (2016). Are elderly consumer more ethnocentric? Attitudes towards Polish and 'foreign' food products. *Journal of Economics and Management*, 23, 91–107.
5. Bhattacharya, S., Sharma, R. P., & Gupta, A. (2023). Does e-retailer's country of origin influence consumer privacy, trust and purchase intention? *Journal of Consumer Marketing*, 40(2), 248–259. <https://doi.org/10.1108/JCM-04-2021-4611>.
6. Bianchi, C., & Mortimer, G. (2015). Drivers of local food consumption: a comparative study. *British Food Journal*, 117(9), 2282–2299. <https://doi.org/10.1108/BFJ-03-2015-0111>.
7. Birch, D., Memery, J., & Kanakaratne, M. (2018). The mindful consumer: Balancing egoistic and altruistic motivations to purchase local food. *Journal of Retailing and Consumer Services*, 40, 221–228. <https://doi.org/10.1016/j.jretconser.2017.10.013>.
8. Bodescu, D., & Moraru, R. (2022). Analysis of some specific features of the local food market in Romania. *Scientific Papers Series Management Economic Engineering in Agriculture and Rural Development*, 22(1), 43–52.
9. Brozzi, R., Stawinoga, A., Hofman, C., & Streifeneder, T. (2016). Determinants of local food purchase Insight from a consumer survey in South Tyrol (Italy). *Socio. hu Társadalomtudományi Szemle*, 99–115. <https://doi.org/10.18030/socio.hu.2016en.99>.
10. Bryła, P. (2015). The role of appeals to tradition in origin food marketing. A survey among Polish consumers. *Appetite*, 91, 302–310. <https://doi.org/10.1016/j.appet.2015.04.056>.
11. Bryła, P. (2019). Regional ethnocentrism on the food market as a pattern of sustainable consumption. *Sustainability*, 11(22), Article 6408. <https://doi.org/10.3390/su11226408>.
12. Bryła, P., & Domański, T. (2023). *Consumer Ethnocentrism, country of origin and marketing: Food market in Poland*. Routledge.
13. Camacho, L. J., Ramírez-Correa, P. E., & Salazar-Concha, C. (2021). Consumer ethnocentrism and country of origin: Effects on online consumer purchase behavior in times of a pandemic. *Sustainability*, 14(1), Article 348. <https://doi.org/10.3390/su14010348>.
14. Čvirik, M., & Dotong, E. (2024). Examining the adaptability of consumer ethnocentrism using CETSCALE: a comparison of the Philippines, Slovakia, and the Czech Republic. *Socijalna Ekologija: Časopis za Ekološku Misao i Sociologijska Istraživanja Okolin*, 33(1), 31–56. <https://doi.org/10.17234/SocEkol.33.1.2>.
15. Czine, P., Balogh, P., Török, Á., & Maró, Z. M. (2024). The role of ethnocentrism in relation to national and geographical indication products—The case of Hungarian palinka. *Journal of Agriculture and Food Research*, 18, Article 101344. <https://doi.org/10.1016/j.jafr.2024.101344>.
16. da Costa Marques, S. C., Mauad, J. R. C., de Faria Domingues, C. H., Borges, J. A. R., & da Silva, J. R. (2022). The importance of local food products attributes in Brazil consumer's preferences. *Future Foods*, 5, Article 100125. <https://doi.org/10.1016/j.fufo.2022.100125>.
17. Dąbrowska, A. (2018). Zachowania konsumentów na rynku żywnościowych produktów tradycyjnych i regionalnych. *Handel Wewnętrzny*, 3(374), 106–117.
18. Drabik, I. (2022). Efekt kraju pochodzenia produktu w strategii przedsiębiorstwa na rynkach zagranicznych. *Przedsiębiorczość – Edukacja*, 18(2), 33–45. <https://doi.org/10.24917/20833296.191.3>.
19. Ehrenberg, A. S. C. (1988). *Repeat Buying: Theory and Applications*. London: Charles Griffin & Company LTD; New York: Oxford University Press. <https://www.empgens.com/wp-content/uploads/2000/06/RB-1-5.pdf>.
20. E.I.T. Food. (2020). *COVID-19 impact on consumer food behaviours in Europe*. https://www.eitfood.eu/media/news-pdf/COVID-19_Study_-_European_Food_Behaviours_-_Report.pdf.

21. Forsal.pl. (2021, November 11). Większym patriotyzmem konsumenckim wykazują się osoby młode oraz kobiety. Retrieved July 19, 2024 from <https://forsal.pl/biznes/handel/artykuly/8290084,wikszym-patriotyzmem-konsumentenckim-wykazuja-sie-osoby-mlode-oraz-kobiety.html>.
22. Gebhardt, B., Deixler, I., Wißmann, I., Jungmair, J. A., & Pöchtrager, S. (2020). Exzellenz in der österreichischen und deutschen Molkereibranche–ein Vergleich. Die Bodenkultur. *Journal of Land Management, Food and Environment*, 71(2), 101–120. <https://doi.org/10.2478/boku-2020-0010>.
23. Gupta, S. (2024). Consumer Ethnocentrism and its Impact on Purchase Intention of Foreign Apparel Brands: Moderating Effect of Demographics. *International Journal of Engineering and Management Research*, 14(4), 43–62. <https://doi.org/10.5281/zenodo.13309466>.
24. Han, B. (2023). The relationship between perceived brand globalness/localness and purchase intention: exploring the role of consumer-brand identification with underdog positioning. *Journal of Product & Brand Management*, 32(4), 632–644. <https://doi.org/10.1108/JPBM-02-2022-3868>.
25. Hanus, G. (2020). Ethnocentrism in Polish consumer food behaviour as a determinant of short supply chain development. *European Journal of Sustainable Development*, 9(4), Article 169. <https://doi.org/10.14207/ejsd.2020.v9n4p169>.
26. Helly, H., Budhi, H., & Didik, S. (2022). The Antecedents of On Purchase Intention of Foreign Products, Mediating Role of Attitude, and the Moderating Role of Ethnocentrism. *International Journal of Economics and Business*, 1(1), 14–27. <https://doi.org/10.59092/ijebi.voll.Iss1.7>.
27. Jadach, R. (2021). Badanie etnocentrycznych zachowań zakupowych nabywców w Polsce. In M. Urbaniec, M. Kosała, & I. Czaja (Eds.), *Bezpieczeństwo ekonomiczne. Polityka, finanse i innowacje* (pp. 215–231). Warszawa: Poltext. https://conference2020.uek.krakow.pl/wp-content/uploads/2020/12/Poltext-Bezpieczenstwo-ekonomiczne_e-book-PDF.pdf.
28. Kaczmarek, M., & Wieja, M. (2021). *Patriotyzm konsumencki Polaków*. Wydawnictwo Uniwersytetu Ekonomicznego w Poznaniu, Poznań.
29. Kamińska, M., & Krakowiak-Drzewiecka, M. (2023). Młodzi konsumenci w społeczeństwie konsumpcyjnym-wnioski z badań. *Prace Naukowe Uniwersytetu Ekonomicznego we Wrocławiu*, 67(1), 46–63. <https://doi.org/10.15611/pn.2023.1.03>.
30. Karoui, S., & Khemakhem, R. (2019). Consumer ethnocentrism in developing countries. *European Research on Management and Business Economics*, 25(2), 63–71. <https://doi.org/10.1016/j.iedeen.2019.04.002>.
31. Kowalska, A. (2011). Food quality and its conditionings. *Acta Scientiarum Polonorum. Oeconomia*, 10(4), 43–54.
32. Kowalska, A., Lingham, S., Maye, D., & Manning, L. (2023). Food Security Through the COVID-19 Crisis and Beyond – Poland: A Case Study in Bukalska, E., Kijek, T. & Sergi, B.S. Eds. *Modeling Economic Growth in Contemporary Poland (Entrepreneurship and Global Economic Growth)* (pp. 89–108). Emerald Publishing Limited. <https://doi.org/10.1108/978-1-83753-654-220231006>.
33. Kovács, I., Balázsne Lendvai, M., & Beke, J. (2022). The importance of food attributes and motivational factors for purchasing local food products: Segmentation of young local food consumers in Hungary. *Sustainability*, 14(6), Article 3224. <https://doi.org/10.3390/su14063224>.
34. Khavari, S., Hosseini, M. H., Khademi, S. M., & Ghamkhari, S. M. (2024). Conceptual model of consumer nationalism with emphasis on resistance economics using metasynthesis and fuzzy Delphi approach. *Consumer Behavior Studies Journal*, 11(1), 1–24. <https://doi.org/10.22034/cbsj.2024.137545.2364>.
35. Maesano, G., Di Vita, G., Chinnici, G., Pappalardo, G., & D'amico, M. (2020). The role of credence attributes in consumer choices of sustainable fish products: A review. *Sustainability*, 12(23), Article 10008. <https://doi.org/10.3390/su122310008>.

36. Maksan, M. T., Kovačić, D., & Cerjak, M. (2019). The Influence of Consumer Ethnocentrism on Purchase of Domestic Wine: Application of the Extended Theory of Planned Behaviour. *Appetite*, 142, Article 104393. <https://doi.org/10.1016/j.appet.2019.104393>.
37. Manning, L., & Kowalska, A. (2021). Considering Fraud Vulnerability Associated with Credence-Based Products Such as Organic Food. *Foods*, 10(8), Article 1879. <https://doi.org/10.3390/foods10081879>.
38. Massey, M., O'Cass, A., & Otahal, P. (2018). A meta-analytic study of the factors driving the purchase of organic food. *Appetite*, 125, 418–427. <https://doi.org/10.1016/j.appet.2018.02.029>.
39. Merle, A., Herault-Fournier, C., & Werle, C. O. C. (2016). The effects of indication of local geographical origin on food perceptions. *Recherche et Applications en Marketing (English Edition)*, 31(1), 26–42. <https://doi.org/10.1177/2051570715626367>.
40. Miftari, I., Cerjak, M., Tomic Maksan, M., Imami, D., & Prenaj, V. (2021). Consumer ethnocentrism and preference for domestic wine in times of COVID-19. *Studies in Agricultural Economics*, 123(3), 103–113. <https://doi.org/10.7896/j.2173>.
41. Migliore, G., Rizzo, G., Schifani, G., Quatrosi, G., Vetri, L., & Testa, R. (2021). Ethnocentrism effects on consumers' behavior during COVID-19 pandemic. *Economies*, 9(4), Article 160. <https://doi.org/10.3390/economies9040160>.
42. Miguel, L. P., Marques, S. H., & Duarte, A. P. (2023). Characterising the fruit and vegetables consumer ethnocentrism in a southern European Country: An assessment of the reliability and validity of the “CETSCALE” in Portugal. *Food Quality and Preference*, 105, Article 104770. <https://doi.org/10.1016/j.foodqual.2022.104770>.
43. Muća, E., Pomianek, I., & Peneva, M. (2021). The Role of GI Products or Local Products in the Environment—Consumer Awareness and Preferences in Albania, Bulgaria and Poland. *Sustainability*, 14(1), Article 4. <https://doi.org/10.3390/su14010004>.
44. Mukucha, P. & Jaravaza, D. C. (2021). Global fast food brands: The role of consumer ethnocentrism in frontier markets. *Journal of Industrial Distribution & Business*, 12(6), 7–21.
45. Nestorowicz, R., Rogala, A., Jerzyk, E., & Pilarczyk, B. (2020). Demographic Determinants of Consumer Ethnocentrism on the Food Market in Poland, in *Eurasian Business Perspectives: Proceedings of the 23rd Eurasia Business and Economics Society Conference*, Springer International Publishing. pp. 251–260. https://doi.org/10.1007/978-3-030-40160-3_18.
46. Newman, C. L., Turri, A. M., Howlett, E., & Stokes, A. (2014). Twenty years of country-of origin food labeling research: A review of the literature and implications for food marketing systems. *Journal of Macromarketing*, 34, 505–519. <https://doi.org/10.1177/0276146714529306>.
47. Nguyen, N. H., Dao, T. K., Duong, T. T., Nguyen, T. T., Nguyen, V. K., & Dao, T. L. (2023). Role of consumer ethnocentrism on purchase intention toward foreign products: Evidence from data of Vietnamese consumers with Chinese products. *Heliyon*, 9(2). <https://doi.org/10.1016/j.heliyon.2023.e13069>.
48. Nolan, K., & Hobbs, J. E. (2023). Signaling Origin: Consumer Perceptions of Product of Canada and Made in Canada Food Labels. *Journal of Food Products Marketing*, 29(5), 155–175. <https://doi.org/10.1080/10454446.2023.2222069>.
49. PMR. (2019). *Handel detaliczny artykułami spożywczymi w Polsce 2019*. <https://mypmr.pro/products/handel-detaliczny-artykulami-spozywczyymi-w-polsce>.
50. Ramadania, R., Suh, J., Rosyadi, R., Purmono, B. B., & Rahmawati, R. (2023). Consumer ethnocentrism, cultural sensitivity, brand credibility on purchase intentions of domestic cosmetics. *Cogent Business & Management*, 10(2), Article 2229551. <http://dx.doi.org/10.1080/23311975.2023.2229551>.
51. Řezanková, H., Hinčica, V., Macias, K., & Jakubová, D. (2023). Ethnocentrism among consumers in selected central European countries: A detailed assessment of ethnocentric patterns.

- Management: Journal of Contemporary Management*, 28(2), 167–184. <https://doi.org/10.30924/mjcmi.28.2.12>.
52. Roy, H. (2022). Local Food, Slow Food, and the Small Farm Movement. in *The Palgrave Handbook of Global Sustainability* (pp. 1–24). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-031-01949-4_46.
 53. Roy, H., & Ballantine, P. W. (2020). Preferences and attitudes toward locally produced food sourcing in wholesale distributors: Restaurant and chef perspectives. *Journal of Hospitality and Tourism Management*, 45, 544–558. <https://doi.org/10.1016/j.jhtm.2020.10.011>.
 54. Russomanno, J., & Tree, J. (2021). Assessing sense of community at farmers markets: A systematic review. *Journal of Agriculture, Food Systems, and Community Development*, 10(2), 489–506. <https://doi.org/10.5304/jafscd.2021.102.032>.
 55. Rytkönen, P. I., Skoglund, W., Pejvak Oghazi, P., & Laven, D. (2024). Exploring the dynamics of innovation: patterns of growth and contraction in the local food industry. *British Food Journal*, 126(13), 1–17. <https://doi.org/10.1108/BFJ-06-2023-0491>.
 56. Sampalean, N. I., Rama, D., & Visent, G. (2021). An investigation into Italian consumers' awareness, perception, knowledge of European Union quality certifications, and consumption of agri-food products carrying those certifications. *Bio-based and Applied Economics*, 10(1), 35–49. <https://doi.org/10.36253/bae-9909>.
 57. Skallerud, K., & Wien, A. H. (2019). Preference for local food as a matter of helping behaviour: Insights from Norway. *Journal of Rural Studies*, 67, 79–88. <https://doi.org/10.1016/j.jrurstud.2019.02.020>.
 58. Stein, A. J., & Santini, F. (2022). The sustainability of “local” food: A review for policy-makers. *Review of Agricultural, Food and Environmental Studies*, 103(1), 77–89. <https://doi.org/10.1007/s41130-021-00148-w>.
 59. Smoluk-Sikorska, J., Wojciechowska-Solis, J., Śmiglak-Krajewska, M., & Malinowski, M. (2024). *Rozwój rynku żywności ekologicznej a zachowania konsumentów*. Wydawnictwo Naukowe Scholar.
 60. Suhartanto, D., Dean, D., Edi Arsawan, I. W., Pradana, M., & Farhani, I. (2024a). Eating good food and helping the community: The drivers of online local food purchasing. *Journal of International Food & Agribusiness Marketing*, 36(4), 665–685. <https://doi.org/10.1080/08974438.2023.2190737>.
 61. Suhartanto, D., Dean, D., & Farhani, I. (2024b). E-grocery service loyalty: integrating food quality, e-grocery quality and relationship quality (young customers' experience with local food). *International Journal of Quality and Service Sciences*, 16(1), 87–102. <https://doi.org/10.1108/IJQSS-06-2023-0080>.
 62. Szabuniewicz, J., & Majkut, R. (2021). Etnocentryzm konsumencki wśród polskich konsumentów w dobie pandemii koronawirusa COVID-19. *Przegląd Organizacji*, 12, 38–47. <https://doi.org/10.33141/po.2021.12.05>.
 63. Szwed, M. (2018). Etnocentryzm konsumencki przedstawicieli pokoleń X, Y i Z w Polsce, in. Nowak, A.Z. & Glinka, B. (Ed.), *Procesy zarządzania w globalizującej się gospodarce*. Wydawnictwo Naukowe Wydziału Zarządzania Uniwersytetu Warszawskiego.
 64. Śliwa, M. (2022). Economic patriotism among people under 35 in Poland in the face of globalization. *Catallaxy*, 7(1), 33–44. <https://orcid.org/0000-0002-7911-9658>.
 65. Thøgersen, J. (2023). How does origin labelling on food packaging influence consumer product evaluation and choices? A systematic literature review. *Food Policy*, 119, Article 102503. <https://doi.org/10.1016/j.foodpol.2023.102503>.
 66. Thomas, T., Singh, N., & Ambady, K. G. (2020). Effect of ethnocentrism and attitude towards foreign brands in purchase decision. *Vision*, 24(3), 320–329. <https://doi.org/10.1177/0972262919867509>.

67. Trivedi, S. D., Tapar, A. V., & Dharmani, P. (2024). A systematic literature review of the relationship between consumer ethnocentrism and product evaluation. *Journal of International Consumer Marketing*, 36(1), 41–61. <https://doi.org/10.1080/08961530.2023.2180790>.
68. UN-Habitat. (2023). *United Nations Human Settlements Programme Annual Report 2022*. Retrieved July, 20 2024 from https://unhabitat.org/sites/default/files/2023/06/unhabitat_annualreport_2022.pdf.
69. Van Bussel, L. M., Kuijsten, A., Mars, M., & Van't Veer, P. (2022). Consumers' perceptions on food-related sustainability: A systematic review. *Journal of Cleaner Production*, 341, Article 130904. <https://doi.org/10.1016/j.jclepro.2022.130904>.
70. Vuong, B. N., & Khanh Giao, H. N. (2020). The impact of perceived brand globalness on consumers' purchase intention and the moderating role of consumer ethnocentrism: An evidence from Vietnam. *Journal of International Consumer Marketing*, 32(1), 47–68. <https://doi.org/10.1080/08961530.2019.1619115>.
71. Witek-Hajduk, M. K., & Grudecka, A. (2022). Does the developed-country brand name still matter? Consumers' purchase intentions and ethnocentrism and materialism as moderators. *Journal Product & Brand Management*, 31(6), 854–869. <https://doi.org/10.1108/IPBM-05-2021-3475>.
72. Weber, H., Loschelder, D. D., Lang, D. J., & Wiek, A. (2021). Connecting consumers to producers to foster sustainable consumption in international coffee supply—a marketing intervention study. *Journal of Marketing Management*, 37(11-12), 1148–1168. <https://doi.org/10.1080/0267257X.2021.1897650>.
73. Wojciechowska-Solis, J. (2022). Consumer Ethnocentrism on the Market for Local Products: Determinants of Consumer Behaviors. *Problems of Agricultural Economics*, 37(4), 75–92. <https://doi.org/10.30858/zer/155842>.
74. Wojcieszak-Zbierska, M. (2021). Krótkie łańcuchy dostaw szansą dla lokalnych przedsiębiorców rolnych. *Turystyka i Rozwój Regionalny*, 15, 139–149. <https://doi.org/10.22630/TIRR.2021.15.13>.
75. Yonfá-Medrandá, M., Sabando-Vera, D., Pérez-Gálvez, J., & Jara-Alba, C. (2024). Consumer ethnocentrism: bibliometric analysis and literature review through cognitive structure and mapping of research based on web of science (WoS) and scopus. *Cogent Business & Management*, 11(1), Article 2377320. <https://doi.org/10.1080/23311975.2024.2377320>.
76. Yu, S. X., Zhou, G., & Huang, J. (2022). Buy domestic or foreign brands? The moderating roles of decision focus and product quality. *Asia Pacific Journal of Marketing and Logistics*, 34(4), 843–861. <https://doi.org/10.1108/APJML-04-2020-0210>.
77. Zhang, T., Grunert, K. G., & Zhou, Y. (2020). A values–beliefs–attitude model of local food consumption: An empirical study in China and Denmark. *Food Quality and Preference*, 83, Article 103916. <https://doi.org/10.1016/j.foodqual.2020.103916>.
78. Zhao, Y., & Wise, N. (2019). Evaluating the intersection between “green events” and sense of community at Liverpool's Lark Lane Farmers Market. *Journal of Community Psychology*, 47(5), 1118–1130. <https://doi.org/10.1002/jcop.22177>.
79. Zhu, D., Du, H., Zhou, G., Hu, M., & Huang, Z. (2025). The Spatiotemporal Dynamics and Evolutionary Relationship Between Urbanization and Eco-Environmental Quality: A Case Study in Hangzhou City, China. *Remote Sensing*, 17(9), 1567. <https://doi.org/10.3390/rs17091567>.

Financial Impacts of the COVID-19 Pandemic on the Cultural and Creative Industries: Evidence from Taiwan

Liza Lee¹, Ying-Sing Liu^{2,*}

¹ Chaoyang University of Technology, 168, Jifeng E. Rd., Wufeng District, Taichung, 413310, Taiwan
ORCID: 0000-0002-4710-6123
e-mail: lylee@gm.cyut.edu.tw

² Chaoyang University of Technology, 168, Jifeng E. Rd., Wufeng District, Taichung, 413310, Taiwan
ORCID: 0000-0002-3161-2136
e-mail: liuyingsing@yahoo.com.tw

* Corresponding author: Ying-Sing Liu, liuyingsing@yahoo.com.tw

Abstract

In the past, it has been confirmed that the COVID-19 pandemic has had a significant negative impact on the cultural and creative industries (C&CIs), but most of this evidence comes from surveys of small and individual enterprises. To date, no study has focused on a financial review of listed firms. This study examines the impact of the COVID-19 pandemic on the financial and operational status of the C&CIs, focusing on 40 firms listed on the Taiwan Stock Exchange. During the 2015–2023 study period, the five categories of major financial indicators and operational indicators were used to test for the equality of means before and during the COVID-19 pandemic. It was empirically found that during the COVID-19 pandemic, the financial structure, solvency, operating capacity, and profitability of the sample firms changed significantly, but there were no significant changes in cash flows or operational indicators. There has not been a significant deterioration in the financial structure of the digital gaming industry (DGI), which has emphasised digitalisation. Although their profitability improved, they did not find the effect to be as significant as expected. The non-DGI group had significantly increased debt ratios and long-term fund-to-fixed-asset ratios, whereas their profitability decreased significantly. This evidence provides some support for the advantages and robustness of DGI in terms of financial performance during the COVID-19 pandemic. The combination of digital technology and securities market fundraising was beneficial to the development of the C&CIs, which were better able to cope with the risks arising from certain unknown and irresistible major events.

Key words

COVID-19, financial indicators, cultural and creative industries, digital game industry, publicly traded company.

Cite as:

Lee, L., & Liu, Y.-S. (2025). Financial Impacts of the COVID-19 Pandemic on the Cultural and Creative Industries: Evidence from Taiwan. *Forum Scientiae Oeconomia*, 13(3), 131–155. https://doi.org/10.23762/FSO_VO_L13_NO3_6

Received: 29 May 2025

Revised: 15 August 2025

Accepted: 20 September 2025



Copyright: © 2025 by the authors. For open-access publication within the terms and conditions of the Creative Commons Attribution (CC BY) licence (<https://creativecommons.org/licenses/by/4.0/>).

Introduction

Coronavirus disease 2019 (COVID-19) has recently become one of the most infectious diseases in the world, resulting in a widespread global pandemic from 2020 to 2022. The number of infections (over 600 million) has had a significant effect on people's livelihoods and economic development. Fortunately, the World Health Organisation (WHO) announced in 2023 that it would no longer consider the COVID-19 pandemic a public health emergency, marking a significant milestone in the fight against the epidemic. During the 2020–2022 pandemic, governments around the world adopted several antiepidemic policies to prevent the spread of the virus, including restricting travel and access to public places, working and attending classes from home, and

preventing people from entering and leaving cities freely (Kaźmierska-Jóźwiak et al., 2021; Snowball & Gouws, 2022; Lee & Liu, 2024). These policies restrict people's daily lives and activity space, affecting many economic activities and industry operations.

Numerous studies have confirmed the impact of the COVID-19 pandemic and other major infectious disease events on specific industries. The results revealed that these epidemics had varying directions and degrees of impact on different industries, and most were concluded to have had negative impacts. Examples include finance-related industries (Elnahass et al., 2021; Ullah, 2023; Liu, 2025a), the film industry (Lee & Liu, 2024), tourism (Liu & Lee, 2022a), and aviation (Rababah et al., 2020). However, some studies on the environmental protection industry (Zhang & Fang, 2022) and the logistics industry (Atayah et al., 2022) have reported positive findings. Nonetheless, some studies confirmed the divergence of views on the impact among hospital peers (Wang et al., 2022). Some studies on the C&CIs tend to reveal a negative impact (Snowball & Gouws, 2022; Kantor & Kubiczek, 2021), especially in terms of the music industry, festivals, and cultural events (Khlystova et al., 2022). However, there was evidence of a positive impact on creative industries related to IT and software (Khlystova et al., 2022). This evidence suggests that the impact of the epidemic on the C&CIs may vary in degree and direction among peers.

Past studies on the impact of the COVID-19 pandemic on the C&CIs have been limited to financial performance, and there is still a lack of extensive reviews of companies' financial and operational health. This study focuses on companies classified as cultural or creative stocks in the Taiwanese stock market, presenting empirical evidence based on annual financial statements and basic operating data released by these companies. These financial data were prepared by the company in accordance with the International Financial Reporting Standards (IFRS), audited and verified by a registered and qualified accountant, and published in accordance with government regulations, which lends them a certain degree of credibility and reference. The objectives of this study are as follows: 1) to explore the impact of the COVID-19 pandemic on industry through a review of corporate finance and operational fundamentals in the C&CIs. 2) Financial structure, solvency, operating ability, profitability, and cash flows (20 items in total) are tested on the basis of the five categories of major financial indicators, and firms' basic operational indicators (five items) are used to understand the impact of the COVID-19 pandemic on finance and operations. 3) The C&CIs are divided into the digital game industry (digital game group) and the remaining C&CIs (nondigital game group), and the test results of each group are used to further compare the groups. 4) The results of the study provide some reference for the financial planning and management of the C&CIs in the face of similar emergencies in the future.

The following sections of this paper are as follows: Section 1 presents a literature review, Section 2 presents the methodology, Section 3 presents the research results and discussion, and Section 4 presents the conclusions.

1. Literature review

Corporate sustainability has been a hot topic in recent years (Meuer et al., 2020; Grewal & Serafeim, 2020; Ardito, 2023; Skocdopole et al., 2023). However, business failure can affect the sustainable operation of enterprises (Amankwah-Amoah et al., 2021) and lead to market exit. One type of business failure is caused by sudden, unpredictable, and difficult-to-mitigate events (Petrucci & Milanesi, 2022). These major events and extreme environmental shocks (such as those caused by the COVID-19 pandemic and other global crises) have caused businesses to suddenly disappear or gradually face bankruptcy and failure. Numerous studies have confirmed that a firm's financial factors are among the primary reasons for business failure. Schalck and Yankol-Schalck (2021) confirmed the role of financial variables in predicting business failure, linking the important relationship between a firm's finances and business failure. Shpak et al. (2022) proposed assessing the financial status of enterprises to ensure their viability and reduce business failure. The risk of old firms closing down due to poor financial conditions is increasing again (Kücher et al., 2020). Dörr et

al. (2022) reported that Germany's COVID-19 policy response triggered a backlog of business failure, which was particularly pronounced among financially weak small firms. In addition, Ellul et al. (2020) explored the COVID-19 pandemic and corporate finance with three themes. First, businesses were able to raise substantial external financing through bank loans and access to public markets, a “dash for cash” in the early stages of the pandemic. Second, the impact of COVID-19 and the related lockdown on firms' liquidity and equity position was considered. As firms navigate the COVID-19 pandemic, they face significant hurdles, including equity shortfalls and debt overhangs, which could potentially lead to zombie lending issues. Third, they studied the firm characteristics (e.g. the firm's balance sheet and business models) that caused the stock prices of firms to react in the early stages of the pandemic. These are larger firms. However, due to the particularities of some smaller firms and cultural products in the C&CIs, it is generally not easy to raise funds through financial institutions or by issuing securities. Therefore, crowdfunding is a unique fundraising method for cultural and creative firms (Handke & Dalla Chiesa, 2022). Konhäusner et al. (2021) took the C&CIs of digital entertainment as an example, using crowdfunding as an alternative financing method to realise projects. They discussed the different benefits that crowdfunding brings to the organisations that run the campaigns.

1.1 Corporation Finance and Operational Fundamentals

Many studies in the past have focused on the financial performance of companies, highlighting the importance of corporate finance. Kyere and Ausloos (2021) examined the corporate governance mechanisms of the UK non-financial listed industry based on two financial performance indicators: return on assets (ROA) and Tobin's Q, and reported a significant relationship between corporate governance and financial performance. Cho et al. (2019) linked the relationship between corporate social responsibility (CSR) and corporate financial performance. Ekinici and Poyraz (2019) confirmed a negative correlation between credit risk and financial performance in the banking sector. Iqbal et al. (2019) analysed the relationship between corporate governance and the financial performance of Asian MFIs, identifying a bidirectional relationship between the corporate governance index and five financial performance indicators. Specifically, profitability and sustainability improved with good governance practices. In addition, we address the operational fundamentals. Lin et al. (2021) explored the impact of firm characteristics (firm size and revenue) on firm financial performance (ROA and return on equity (ROE)). Achim et al. (2022) reported that equity financing, effective liquidity management, and expansion of firm size during the COVID-19 pandemic underpinned the performance of ROE and ROA. Zhou et al. (2022) confirmed that improving a firm's ESG performance can increase the company's market value.

1.2 Impact of the COVID-19 Pandemic on the Market or Industry

Many studies have confirmed that the COVID-19 pandemic will have different impacts on different markets or industries. For example, in a European listed company, Mahssouni et al. (2023) reported that COVID-19 had a significant negative impact on financial performance, as measured by ROA and ROE. Liu and Lee (2022b) confirmed a significant increase in the systemic risk of Yuanta's Shanghai Stock Exchange 50 ETF traded in the Taiwan securities market following the COVID-19 pandemic, as well as a significant reduction in the fund's asset size. Chen and Liu (2023) examined the impact of the late COVID-19 pandemic on Taiwan's stock market, finding that stock price reactions varied across different markets and industries. The stock exchange market (SEM) has decreased, while the over the counter (OTC) market has increased. Meanwhile, the sports and prevention industries have decreased, and the restaurants and biotechnology industries have increased. Smrt et al. (2025) confirmed that the COVID-19 pandemic had a significant impact on stock prices in the global video game industry. Ullah (2023) confirmed that new COVID-19 information will have a negative impact on the daily returns of financial markets worldwide. Achim et al. (2022) reported that during the COVID-19 pandemic, net profit decreased by 37.43% across the market. However, smaller companies in agriculture, commerce, construction, IT research and development, and transportation and warehousing performed better financially.

Among SMEs, Rababah et al. (2020) reported that the financial performance of Chinese listed companies has been most affected by the COVID-19 pandemic, with tourism and aviation being the most affected. Elnahass et al. (2021) confirmed that the outbreak of COVID-19 has adversely affected the financial performance and financial stability of the global banking sector. Song et al. (2021) examined the impact of COVID-19 on the stock returns of U.S. restaurant companies and reported that international restaurant companies that used to be larger, more leveraged, have greater cash flow, and lower ROA were more resilient to COVID-19. Zhang and Fang (2022) reported that environmental protection companies performed better during the COVID-19 pandemic, while SMEs were less vulnerable than large enterprises were. The evidence suggests that the severity of the damage caused by COVID-19 depends on the size of the company and the investment in pollution abatement technologies. Environmentally friendly SMEs have been less affected by the pandemic, which may be related to the effectiveness of the government's relief programs for environmentally friendly SMEs. Atayah et al. (2022) investigated the correlation between the financial performance of listed logistics companies and COVID-19, and the results revealed that the financial performance of logistics companies was significantly greater in 2020. Finally, Wang et al. (2022) evaluated the changes in the financial performance of California hospitals related to the COVID-19 pandemic and reported that the impact on hospital finances was diverse, and they agreed that government assistance programs mitigated the economic losses of hospitals.

1.3 Cultural and Creative Industries

Many studies have confirmed the importance of culture and the arts, as well as their vulnerability to economic shocks (Shin, 2025). Protogerou et al. (2022) reported that adverse economic conditions (COVID-19) contribute to the characteristics of creative industries: 1) highly international entrepreneurial teams with extensive overseas work and study experience and 2) companies that also combine creative expertise with management and marketing expertise. 3) Export oriented, able to serve a diverse customer base, and invest in digital technologies. Snowball and Gouws (2022) argued that lockdown rules and social distancing policies imposed by the COVID-19 pandemic had a negative effect on C&CIs in these countries. Kantor and Kubiczek (2021) explored the impact of the COVID-19 pandemic on the activities of cultural institutions and reported that the pandemic has reduced the income of cultural institutions, leading to a significant deterioration in their financial situation. Che Arshad and Irijanto (2023) reported that the creative industries contributed to the economic growth of Association of Southeast Asian Nations (ASEAN) countries during the COVID-19 pandemic, as the Sukuk bond market played a significant role in driving economic growth. Escalona-Orcao et al. (2021) explored the impact of the COVID-19 pandemic on the cultural and creative ecosystems of 81 cities in Spain. Nonmetropolises appear to be more vulnerable, whereas metropolises appear to be safer because of increased and accelerated digitalization.

Khlystova et al. (2022) revealed several positive impacts of the COVID-19 pandemic on creative industries (IT and software), as well as negative impacts on the music industry, festivals, and cultural events, via a literature review approach. Yue (2022) compared the combination of emergency resilience and ecological resilience that underpins the crisis of C&CIs and proposed that ecological resilience is characterized by a focus on transformation and resilience as a decentralized strategy and networked resources in the long term. Zhang et al. (2022) reported that the pandemic had a significant negative effect on the stock market returns of cultural industries, but there were significant differences in the degree of impact on each creative subsector. The results of the study suggest that digitalisation can effectively reduce the negative impact of COVID-19 on cultural companies, whereas the pandemic has had a greater negative impact on small and newly established cultural companies. Snowball and Gouws (2022) examined the impact of the COVID-19 pandemic on South Africa's Community and Constituency Institutions (C&Cs) through a survey of companies

and freelancers (2020 and 2021), as well as interviews with key stakeholders and a social accounting matrix for South Africa's C&Cs.

Vitálišová et al. (2021) identified and assessed the impact of the COVID-19 pandemic on C&CIs from a national perspective, evaluating the measures taken by governments to mitigate its consequences. Particular attention was given to the financing of the C&CIs, as well as the social impact on different groups of respondents. Wall-Andrews et al. (2021) examined the range of financial instruments (grants and subsidies) created by the Government of Canada during the pandemic to support C&CIs. On the basis of this support, the creative and cultural sector (CCS) has been able to succeed economically and socially, thereby avoiding the risk of collapse in the cultural ecosystem. Peñarroya-Farell and Miralles (2022) proposed a new framework in the context of the COVID-19 pandemic. The framework assumed a better understanding of business model adaptation under emergency management theory and improvisational capabilities. Joffe (2021) explored the impact of the COVID-19 pandemic on the modernisation and development of African cultures. Focusing on South Africa, COVID-19 offers opportunities to guide the cultural economy process in Africa.

Santoro et al. (2020) assess whether formal and informal modes of collaboration with C&CIs affect innovation performance and evaluate the moderating role of combining heterogeneous knowledge sources and absorptive capacity. Jeannotte (2021) proposed a conceptual framework comprising four parts (economic, social, creative, and sustainable) to study the direct impact of the COVID-19 pandemic on creators, curators, and the media, and discussed how governments and citizens evaluate the potential impact of the creative sector. Langevang et al. (2022) demonstrated the factors of digitalisation, diversification, and social engagement through a survey of workers in Ghana's creative industries during the COVID-19 pandemic. Cunningham et al. (2021) examined regional cultural and creative activities in Australia and presented three key findings relevant to the international cultural policy debate.

Bakhshi et al. (2023) conducted a weekly longitudinal survey of UK adults to examine consumption choices in terms of cultural content types during the first COVID-19 national lockdown (the Great Lockdown). Changes in the probability of consuming content across various cultural and creative genres (music, movies, TV, games, books, magazines, and audiobooks), as well as shifts in overall consumption types, were examined. It was found that consumption varies depending on the type of content. All else being equal, the likelihood of listening to music and playing games increases, whereas the likelihood of reading books decreases. The increase in the variety of consumption of people at the bottom of the socioeconomic status distribution confirmed the importance of gaining culture and creativity for this particular social segment during the lockdown. Shin (2025) assessed the extent to which the culture and arts industries had been adversely affected by the COVID-19 pandemic, quantitatively measuring the impact of COVID-19 on the cultural participation of the Korean people. COVID-19 significantly reduced the likelihood of Koreans participating in cultural and artistic activities. However, the pandemic has increased the likelihood that people will visit libraries, and the number of movies watched through digital media has increased.

Dümcke (2021) presented the impact of COVID-19 on the German Ministry of Culture and Creativity (CCS) from March to the end of July 2020, examining German responses (at the federal, state, and municipal levels) in three phases. Williams et al. (2024) examined the effects of COVID-19 on Australia's Tasmanian cultural and creative sector, including its implications for financial sustainability, health and well-being, and the future of work. The results revealed that individuals who received financial support during the pandemic were able to adapt or adjust their creative practices and experienced higher levels of health and well-being. Those who do not receive support have a significant negative impact on their health and creative practices. Finally, Lu and Chesbrough (2022) investigated the relationship between open innovation practices and a firm's financial

performance. The overall level of openness (innovation) of a company is associated with improved financial performance.

1.4 Digital Transformation and Business Models in C&CIs

Zhao et al. (2024) highlighted the digital economy as a new engine for global economic growth, finding that it significantly promotes the development of creative industries, with innovation efficiency playing a partial mediating role between the digital economy and the development of creative industries. Gustafsson and Lazzaro (2021) discussed four major social challenges facing C&CIs and highlighted the significant potential for innovation and smart growth in the EU. These social challenges are addressed by the four main pillars of the C&CI program: (1) European creativity, cultural diversity, and values; (2) European identity and cohesion; (3) European employment, economic resilience, and smart growth; and (4) Europe's external relations. Ryu et al. (2024) noted that traditional C&CIs are increasingly digitalising, with new concepts and business models emerging, such as digital and entertainment labour, the platform economy, media convergence, digital and self-publishing, user participation, and fan culture. The four core themes of the digital transformation of traditional C&CI are as follows: 1) changes in television and video culture; 2) the rise of the platform economy and participatory culture; 3) the transformation of the publishing industry and copyright issues; and 4) the relationship between digital labor and gender equality.

Lerro et al. (2022) highlighted the impacts of digital transformation (DT) on new business models, products and services, supply chain and operational configurations, customer orientation, and new ways of working. Research on digitally driven innovation and entrepreneurship has at least three major limitations. First, it involves theoretical issues, particularly the failure to incorporate a holistic approach beyond the realm of information systems, and the lack of a more interdisciplinary perspective within the management field. Second, few studies have explored how specific organisational characteristics and expertise at the organisational level may influence the adoption of digital technologies and tools, performance improvement, and sustainability. Third, current DT research on innovation and entrepreneurship focuses primarily on large companies and organizations and specific industries (e.g., automotive). Current DT research often emphasizes the challenges of transformation. Numerous digital technologies facilitate innovation opportunities and reduce the time required to create and launch new products and solutions, promoting widespread changes in business models. At the micro level, the focus is on how DT impacts business model innovation, thus influencing entrepreneurial dynamics. Digital technologies and related tools are transforming collaborative innovation (CCI) and fostering the emergence of new entrepreneurial and business models.

Nasta (2025) argued that digital technologies have had a significant impact on the business models and value chains of certain creative industries. He defined digital transformation as the integration of digital technologies into all business areas, fundamentally changing operations and the delivery of value. The key attributes of digital transformation include agility, customer centricity, data-driven decision-making, and fostering a digital culture. Digital transformation radically alters customer relationships, value propositions, distribution channels, revenue streams, key resources, activities, partnerships, and cost structures. It emphasised how digital platforms, data analytics, and personalised experiences enhance customer engagement and market reach while optimising operations. Peñarroya-Farell and Miralles (2022) discussed how many companies, under the impact of the COVID-19 pandemic, survived by adapting their business models through open innovation and leveraging the creative and improvisational capabilities of the cultural industry, thus creating new value to address environmental challenges and strategically responding to the crisis.

Khlystova and Kalyuzhnova (2023) reported that regions with a greater proportion of employees in creative industries are more resilient to short-term economic shocks than regions with a lower proportion. They reported the importance of digitalisation during crisis recovery. Hosseini and Rajabipoor Meybodi (2023) developed an integrated model for the sustainable development of

creative industries through digital transformation and explanatory structural modelling. The model identified key components, including digital technology, cultural values, environmental and industrial intelligence, digital work environments, and digital entrepreneurial ecosystems. They argued that focusing on digital infrastructure, including digital communication, essential technologies, and information security, is crucial for the sustainable development of creative industries, as these are the foundations for fostering creativity in the digital realm. Lazzeretti et al. (2025) argued that the digital revolution has not only permeated and transformed various industrial sectors but also altered society as a whole, leading to new expressions of cultural heritage, increased creative capacity, and the emergence of new market niches. Gao et al. (2024) investigated the relationship between C&CI and sustainable development, reporting a positive correlation between the density of the C&CI network and a city's performance in achieving various sustainable development goals. The relationship between the size of local C&CIs and a city's sustainable development performance was found to be an inverted "U" shape.

2. Methodology

2.1 Empirical Data

C&CIs are industries that combine culture and creativity, and there are special laws and regulations for them in Taiwan to protect and promote development. According to the Cultural and Creative Industries Development Law formulated by the local government, cultural creativity refers to the formation and use of intellectual property derived from creativity or cultural accumulation. The following industries have the potential to create wealth and employment opportunities; promote the aesthetic literacy of all the people; and improve the living environment of the people: visual arts; music and performing arts; cultural asset application and exhibition and performance facilities; crafts; film, radio and television; publishing; advertising; product design; visual communication design; design of brand fashion; architectural design; digital content; creative life; popular music and cultural content; and other industries designed by the Central Competent Authority. According to the 2019 Taiwan Cultural and Creative Development Annual Report, Taiwan's C&CIs account for approximately 4~5% of the overall annual GDP.

This study examines the impact of the COVID-19 pandemic on Taiwan's C&CIs by analysing corporations' financial and operational status. The study included 40 firms classified as C&CI stocks (code: M3200) in the Taiwan stock market, excluding those that had been suspended or ceased trading, as well as firms with insufficient or missing financial information. The condition for the selection of firms to become a sample firm is to be able to obtain the annual financial statements of the firm from before the onset of COVID-19 to the outbreak of the pandemic (2015-2022) (37 firms), and three firms are relaxed to 2016-2022. The structural composition of the subindustries to which these firms belong is shown in Figure 1. The subindustry classification standard here is based on the basic information of the sample firms (TEJ industry name) from the Taiwan Economic Journal Database (TEJD).

Digital games (leisure), which are mainly used in digital content in the software service industry (programming industry), accounted for 42%, and 10 firms in the television broadcasting industry accounted for 25%. The remaining 13 firms are wholesalers of department stores, dealing with manufacturers of stationery, art, and cultural ceramics, as well as pop music creation, advertising, and computer and peripheral manufacturers related to the industry. During the study period, from January 2015 to December 2023, a total of 397 samples were collected, and the observations included annual financial statement data and basic operating conditions of individual firms. The period is divided into five years before the COVID-19 pandemic (2015--2019), three years during the COVID-19 pandemic (2020--2022), and one year after the COVID-19 pandemic (2023). The data source is the "IFRS Finance-International Accounting Standards" database taken from the TEJD. It is a financial database that primarily collects data from Taiwan, Hong Kong, and China, specialising in providing information for fundamental analysis of securities and financial markets.

This data source has been utilised in numerous studies (Chen & Liu, 2022; Chen et al., 2022, 2023; Ding et al., 2024; Yang et al., 2024; Liu, 2021 & 2025b). The period of the COVID-19 pandemic is defined on the basis of the fact that from the first case of infection in Taiwan in the first quarter of 2020 to the end of 2022, the cumulative number of confirmed cases was more than 8.83 million (the local population was approximately 23 million). In 2023, a variety of vaccines were widely administered so that the epidemic could be gradually controlled, and at the same time, people's various life restrictions were gradually relaxed and returned to normal nonepidemic periods.

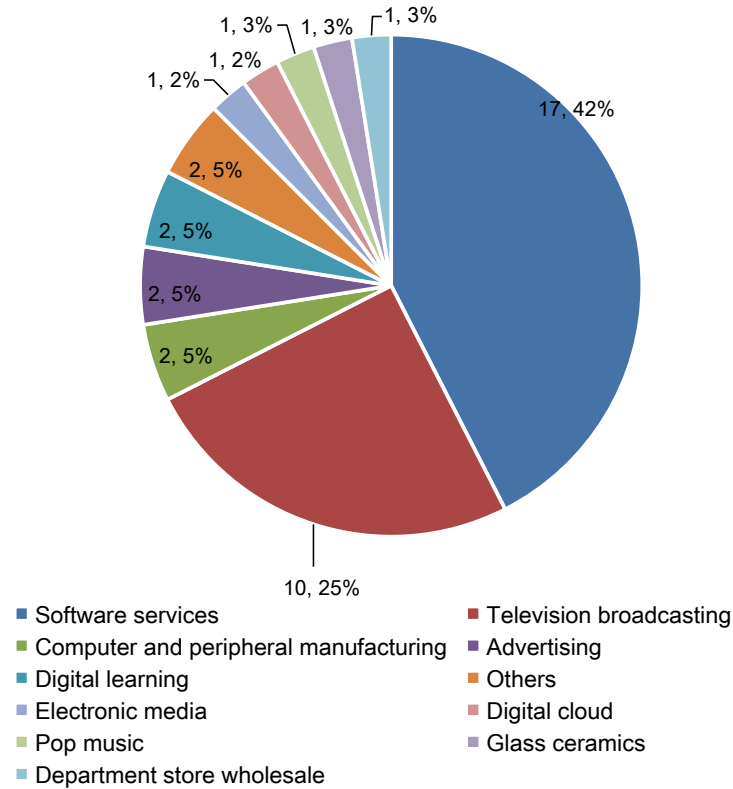


Figure 1. A circular scale chart of the industrial structure of the sample firms.

Source: Own elaboration on the basis of TEJD.

2.2 Study Variables

This study is based on an analysis of five categories of major financial indicators, which measure a firm's 1) financial structure; 2) solvency; 3) operating ability; 4) profitability; and 5) cash flows, with 20 financial indicators. The names, calculation forms, and symbols of the 20 financial indicators are summarised in Table 1. This table facilitates the understanding of each indicator's definition, practical application, and classification within the five established categories of financial indicators. The basic operating status of the firm is based on five indicators: annual operating revenue (NTD thousand), revenue growth rate (%), book value per share (NTD/share), number of employees (person), and paid-in capital (NTD thousand).

Table 1. Symbols and calculation forms of financial indicators.

No.	Financial Indicator	Symbol	Calculating Form (Unit)
1. Financial Structure			
1.1	Debt Ratio	DR_{it}	Total Liabilities/Total Assets $\times 100$ (%)
1.2	Fixed Assets to Total Assets Ratio	$FATAR_{it}$	Net Fixed Assets/Total Assets $\times 100$ (%)
1.3	Long-term Funds to Fixed Assets Ratio	$LFFAR_{it}$	(Shareholders' Equity + Long-term Liabilities)/Net Fixed Assets $\times 100$ (%)
2. Solvency			
2.1	Working Capital to Total Assets Ratio	$WCTAR_{it}$	(Current Assets - Current Liabilities)/Total Assets $\times 100$ (%)

2.2	Current Ratio	CR _{it}	Current Assets/Current Liabilities ×100 (%)
2.3	Quick Ratio	QR _{it}	(Current Assets - Inventories - Prepaid Expenses)/Current Liabilities ×100 (%)
2.4	Cash to Current Liabilities Ratio	CCLR _{it}	(Cash & Cash Equivalents + Short-term Investments)/Current Liabilities ×100 (%)
2.5	Times Interest Earned	TIE _{it}	(Net Profit before Tax + Interest Expense)/Interest Expense (times)
3. Operating Ability			
3.1	Receivables Turnover	RT _{it}	Annual Operating Income/Average Accounts Receivable and Bills for each period (times)
3.2	Inventory Turnover	IT _{it}	Cost of Goods Sold/Average Inventory (times)
3.3	Fixed Asset Turnover Ratio	FATR _{it}	Net sales/Net Fixed Assets ×100 (%)
3.4	Asset Turnover Ratio	ATR _{it}	Net Sales/Total Assets ×100 (%)
4. Profitability			
4.1	Return on Assets	ROA _{it}	[After-tax Profit and Loss + Interest Expense × (1 - Tax Rate)]/Average Total Assets ×100 (%)
4.2	Return on Equity	ROE _{it}	Profit and Loss after Tax/Average Net Shareholders' Equity ×100 (%)
4.3	Profit Margin	PM _{it}	Net Profit(Loss) after Tax/Operating Income ×100 (%)
4.4	Operating Income Margin	OIM _{it}	Operating Profit/Operating Income ×100 (%)
4.5	Earning Per Share	EPS _{it}	(Net Income after Tax - Preferred Stock Dividend)/Weighted Average Number of Shares Outstanding (NTD/share)
5. Cash Flows			
5.1	Cash Flow Ratio	CFR _{it}	Net cash flow from operating activities/current liabilities ×100 (%)
5.2	Cash Flow Adequacy Ratio	CFAR _{it}	Net cash flow from operating activities for the last five years/The sum of capital expenditures, inventory additions, and cash dividends for the last five years ×100 (%)
5.3	Cash Reinvestment Ratio	CRR _{it}	(Net cash flow from operating activities - cash dividends)/(Gross fixed assets + long-term investments + other assets + working capital) ×100 (%)

Source: Own elaboration.

2.3 Testing Methods

This study explored the impact of the COVID-19 pandemic on selected financial and operational indicators by dividing the empirical data into two independent groups: the pre-COVID-19 period and the pandemic period. The population means for each indicator were treated as unknown, and statistical tests were conducted to evaluate whether significant differences existed between the two groups.

Let X denote a study variable, with corresponding population means μ_{preCOV} and μ_{pandemic} for the pre-COVID-19 and pandemic periods, respectively. The hypothesis testing framework was defined as follows:

The null hypothesis $H_0: \mu_{\text{pandemic}} = \mu_{\text{preCOV}}$ (or $\mu_{\text{pandemic}} - \mu_{\text{preCOV}} = 0$) indicates that the pandemic did not significantly affect the mean of the variable.

The alternative hypothesis $H_1: \mu_{\text{pandemic}} \neq \mu_{\text{preCOV}}$ (or $\mu_{\text{pandemic}} - \mu_{\text{preCOV}} \neq 0$) suggests a statistically significant change in the variable's mean due to the pandemic.

When the population variances were unknown and assumed to be equal ($\sigma_{\text{preCOV}}^2 = \sigma_{\text{pandemic}}^2 = \sigma^2$), the difference in means between the pre-COVID-19 and pandemic periods was evaluated via the mean difference t-test for the two independent samples. The test statistic was defined as follows:

$$t = \frac{(\bar{X}_{\text{pandemic}} - \bar{X}_{\text{preCOV}}) - 0}{\hat{S} \cdot \sqrt{\frac{1}{N_{\text{pandemic}}} + \frac{1}{N_{\text{preCOV}}}}} \quad (1)$$

In equation (1), $\bar{X}_{\text{pandemic}}$ and $\bar{X}_{\text{preCOV}}$ are the sample means in the pandemic period and pre-COVID-19 period, respectively. $\hat{S}$ represents the sample standard deviation ($\hat{S}_{\text{preCOV}}^2 = \hat{S}_{\text{pandemic}}^2 = \hat{S}^2$). N_{preCOV} and N_{pandemic} are the group samples from the pandemic and pre-COVID-19 periods, respectively. The null hypothesis $H_0: \mu_{\text{pandemic}} = \mu_{\text{preCOV}}$ (or $\mu_{\text{pandemic}} - \mu_{\text{preCOV}} = 0$) was rejected at the 5% significance level ($\alpha=0.05$) if the

absolute value of the test statistic exceeded the critical value from the t-distribution $|t| > t_{(1-\frac{\alpha}{2}, N_{preCOV}+N_{pandemic}-2)}$.

When the population variances of the two groups were unknown and assumed to be unequal, the mean difference between the two independent samples was tested via the Satterthwaite–Welch t-test (Karim et al., 2023) in the form of

$$t_{SW} = \frac{(\bar{X}_{pandemic} - \bar{X}_{preCOV}) - 0}{\sqrt{\frac{\hat{s}_{pandemic}^2}{N_{pandemic}} + \frac{\hat{s}_{preCOV}^2}{N_{preCOV}}}} \quad (2)$$

In equation (2), $\hat{s}_{preCOV}^2$ and $\hat{s}_{pandemic}^2$ denote the sample variances of the pre-COVID-19 and pandemic periods, respectively. In accordance with the calculation method used by Satterthwaite–Welch, the combined degrees of freedom were

$$v \approx \frac{\left(\frac{\hat{s}_{pandemic}^2}{N_{pandemic}} + \frac{\hat{s}_{preCOV}^2}{N_{preCOV}} \right)^2}{\frac{(\hat{s}_{pandemic}^2/N_{pandemic})^2}{v_{pandemic}} + \frac{(\hat{s}_{preCOV}^2/N_{preCOV})^2}{v_{preCOV}}} \quad (3)$$

In equation (3), $v_{pandemic}$ and v_{preCOV} denote the degrees of freedom of the pandemic and pre-COVID-19 periods, respectively. The inference here was similar to paragraph (1) above and was not repeated.

Finally, using the results of Levene's test for the equality of variances, it can be concluded that the results of the t test ($\sigma_{preCOV}^2 = \sigma_{pandemic}^2$) or the Satterthwaite–Welch t test ($\sigma_{preCOV}^2 \neq \sigma_{pandemic}^2$) were used in the tests for the equality of means, i.e., checking k ($k \geq 2$; this study is $k=2$) to determine whether the number of variances was the same between groups. Here, the null hypothesis was $H_0: \sigma_1^2 = \sigma_2^2 = \dots = \sigma_k^2 = \sigma^2$, whereas the alternative hypothesis was $H_1: \sigma_i^2 \neq \sigma_j^2$, where $i \neq j$, and $1 \leq i, j \leq k$. Assuming that the j -th observation of group i was X_{ij} , $i=1,2,3,\dots,k$, and $j=1,2,\dots,n_i$, n_i was the number of samples in group i . Therefore, the absolute error of the random variable X_{ij} and the mean $\bar{X}_i$ of group i was $Y_{ij} = |X_{ij} - \bar{X}_i|$. This condition was equivalent to one-way ANOVA with a test of the F statistic. The definition was as follows:

$$F = \frac{\frac{\sum_{i=1}^k n_i (\bar{Y}_i - \bar{\bar{Y}})^2}{k-1}}{\frac{\sum_{i=1}^k \sum_{j=1}^{n_i} (Y_{ij} - \bar{Y}_i)^2}{\sum_{i=1}^k (n_i - 1)}} \quad (4)$$

In equation (4), $\bar{Y}_i = \sum_{j=1}^{n_i} Y_{ij} / n_i$ is the mean absolute error of group i . $\bar{\bar{Y}} = \sum_{i=1}^k \sum_{j=1}^{n_i} Y_{ij} / N$ is the mean absolute error, the degrees of freedom are $v_1 = k - 1$ and $v_2 = N - k$, then $N = \sum_{i=1}^k n_i$, and the significance level is $\alpha=0.05$.

3. Research results

3.1 Descriptive Statistics

Table 2 presents descriptive statistics, which estimate the mean $\pm$ standard deviation of 25 basic financial and operational indicators for 40 C&CI firms from 2015 to 2023. The period is divided into three subperiods: pre-COVID-19 (2015-2019), the COVID-19 pandemic (2020-2022), and the post-pandemic (2023), to observe the changes in these indicators before the occurrence of COVID-19, during the pandemic, and after the pandemic.

Table 2. Descriptive statistics.

Indicator	Mean±S.D.			
	Whole period (2015-2023)	Pre-COV-19 (2015-2019)	Pandemic (2020-2022)	Postpandemic (2023)
1.1 DR _{it}	38.896±21.881	38.614±22.136	39.511±21.028	38.389±23.746
1.2 FATAR _{it}	13.244±17.119	13.859±17.555	12.281±16.670	13.129±16.527
1.3 LFFAR _{it}	9521.12±32480.58	5133.41±15318.85	14822.06±48932.29	15453.35±29541.56
2.1 WCTAR _{it}	32.983±32.871	32.993±34.182	32.529±31.068	34.405±32.328
2.2 CR _{it}	320.857±287.639	326.821±315.891	304.778±241.262	341.576±273.927
2.3 QR _{it}	254.129±248.201	251.880±270.661	248.103±209.518	285.521±244.124
2.4 CCLR _{it}	60.194±23.732	55.878±23.015	65.104±24.002	67.023±22.433
2.5 TIE _{it}	783.375±8490.266	204.515±2812.983	813.035±10313.109	3143.425±15286.535
3.1 RT _{it}	12.284±19.582	11.298±18.018	13.539±22.693	13.298±16.400
3.2 IT _{it}	1354.41±15728.69	1894.70±19952.27	890.68±9195.91	69.276±193.975
3.3 FATR _{it}	55.828±112.723	43.322±88.807	68.936±126.609	77.875±161.129
3.4 ATR _{it}	0.690±0.548	0.800±0.612	0.574±0.446	0.500±0.346
4.1 ROA _{it}	-0.679±18.340	-0.226±18.307	-1.012±18.532	-1.934±18.307
4.2 ROE _{it}	-1.898±53.728	4.665±57.419	-8.098±44.498	-14.965±58.286
4.3 PM _{it}	-193.993±2120.260	-21.534±98.612	-497.699±3606.743	-116.790±543.054
4.4 OIM _{it}	-153.992±1685.732	-18.357±87.265	-387.760±2866.234	-109.647±468.902
4.5 EPS _{it}	1.758±7.404	1.612±5.863	2.024±9.165	1.662±8.372
5.1 CFR _{it}	13.639±79.794	14.244±83.914	17.454±71.515	-1.886±83.462
5.2 CFAR _{it}	-209.156±2157.367	-265.974±2193.716	-255.920±2331.611	183.151±1239.377
5.3 CRR _{it}	-7.009±169.406	-13.400±226.277	2.706±21.211	-4.504±24.762
Operating Revenue	1259918.0±2592412.1	1250108.4±2561075.3	1224265.2±2537351.0	1426718.4±2975831.5
Revenue Growth Rate	29.546±171.493	38.637±200.891	12.386±99.065	38.538±192.150
Book Value Per Share	19.001±16.173	19.131±14.657	19.048±18.243	18.163±17.077
Number of Employees	200.716±274.214	200.662±275.037	198.950±272.250	206.730±283.603
Paid in Capital	604994.45±677620.04	605755.66±679239.44	596488.40±674349.16	628569.89±697595.42

Source: Own elaboration.

In Figure 2, histograms were created using the means of the financial indicators from Table 2 to facilitate comparisons of financial changes during the pre-COVID-19 period, the COVID-19 pandemic, and the post-pandemic period.

The financial indicators are divided into five categories:

Financial structure: The means of the debt ratio (DR_{it}), fixed assets to total assets ratio (LFFAR_{it}), and long-term funds to fixed assets ratio (LFFAR_{it}) were 38.896%, 13.244%, and 9,521.12%, respectively. The mean LFFAR_{it} rose markedly from 5,133.41% in the pre-COVID-19 period to 14,822.06% during the pandemic period and further to 15,453.35% in the post-pandemic period. This increase was accompanied by greater variance, indicating elevated financial risk during the pandemic. The results revealed that the average LFFAR_{it} during the pandemic increased while also exacerbating the standard deviation (risk); however, the mean of the indicator did not decrease, but the standard deviation (risk) decreased. In contrast, DR_{it} and FATAR_{it} exhibited relatively minor fluctuations across the three periods, suggesting limited impact from the pandemic.

Solvency: The means of the working capital to total assets ratio (WCTAR_{it}), current ratio (CR_{it}), quick ratio (QR_{it}), cash to current liabilities ratio (CCLR_{it}) and number of times interest earned (TIE_{it}) over the whole period were 32.983%, 320.857%, 254.129%, 60.194% and 783.375 times, respectively. During the COVID-19 pandemic, WCTAR_{it}, CR_{it}, and QR_{it} declined slightly, whereas CCLR_{it} and TIE_{it} increased significantly to 65.104% and 813.035 times, respectively, indicating improved short- and long-term solvency. Finally, the means of these five indicators were greater than those before and during the pandemic (2023), possibly because companies strengthened their control of financial risk management to cope with potential future crises, resulting in improvements in solvency after the pandemic.

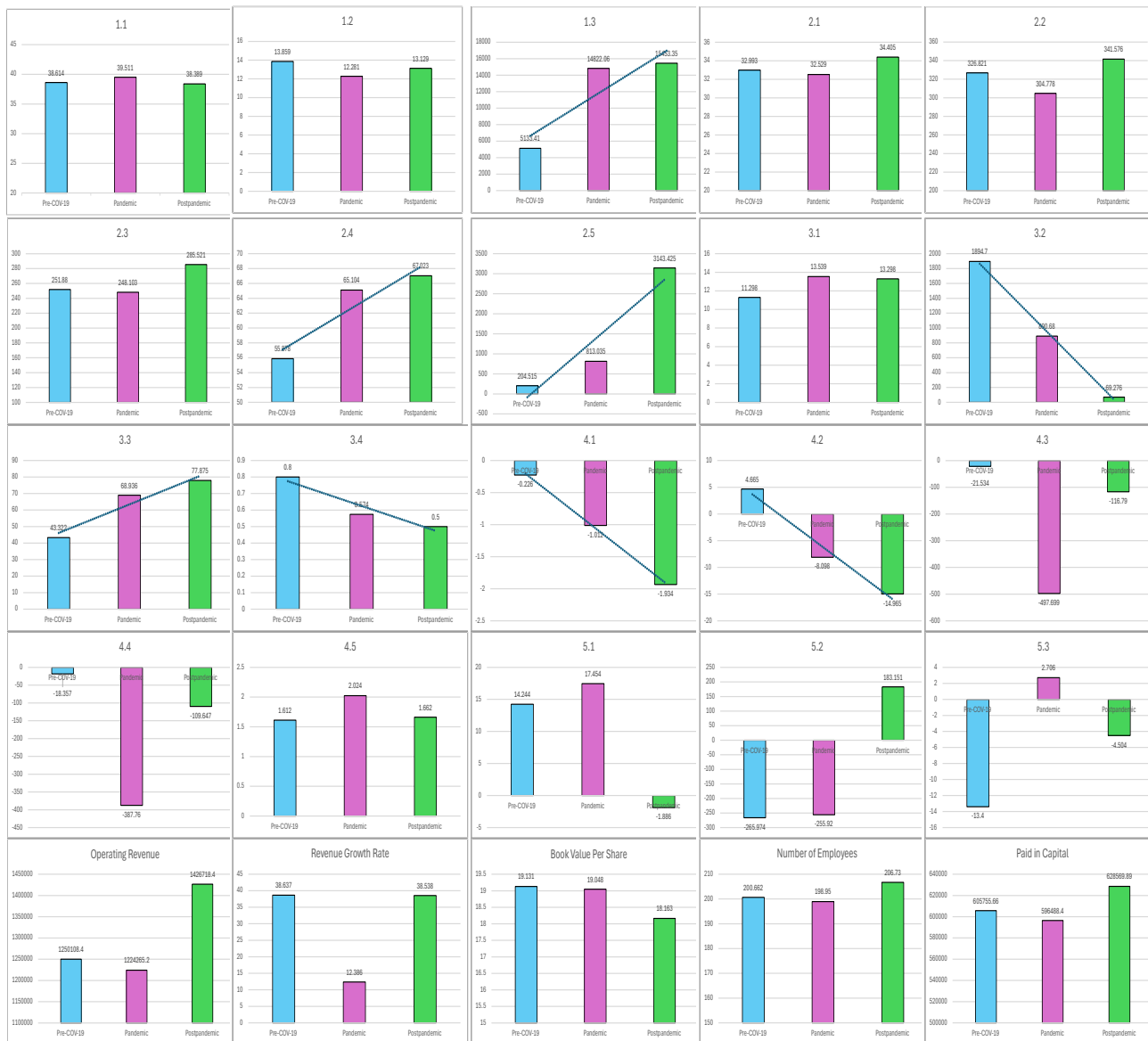


Figure 2. Histogram comparing the means of various financial indicators during the pre-COVID-19 period, the COVID-19 pandemic, and the post-pandemic period.

Source: Own elaboration based on TEJD.

Operating ability: The means of receivable turnover (RT_{it}), inventory turnover (IT_{it} 1,354.41 times), and the fixed asset turnover ratio ($FATR_{it}$ 55.828%), and the asset turnover ratio (ATR_{it} 0.690%) were calculated. The means of IT_{it} and ATR_{it} during the pandemic decreased, but the means of RT_{it} and $FATR_{it}$ increased. This shows that the impact of the epidemic on the indicators of operating ability was inconsistent.

Profitability: The means of ROA (ROA_{it}), ROE (ROE_{it}), profit margin (PM_{it}), operating income margin (OIM_{it}), and EPS (EPS_{it}) were -0.679%, -1.898%, -193.993%, -153.992% and 1.758 NTD/share, respectively; only the mean of EPS_{it} was positive, and the other four indicators were negative, indicating that the average profit level of the industry was a loss. In addition, the means of ROA_{it} , PM_{it} , and OIM_{it} were negative during the pre-COVID-19 period, whereas the negative values worsened during the COVID-19 pandemic, and ROE_{it} changed from positive to negative. These findings indicate that the average profitability of the industry has declined during the pandemic. These results are similar to the arguments of Mahssouni et al. (2023) and Rababah et al. (2020) that the pandemic tends to have a significant negative effect on firms' financial performance. However, the EPS_{it} from the mean before COVID-19 was 1.612 NTD/share during the COVID-19

pandemic, but it increased to 2.024 NTD/share. Finally, the average of these indicators after the pandemic had not fully recovered to the pre-COVID-19 average, especially ROA_{it} and ROE_{it} , which were worse than those during the COVID-19 pandemic, indicating that profitability has not yet recovered.

Cash flows: The means of the cash flow ratio (CFR_{it}), cash flow adequacy ratio ($CFAR_{it}$), and cash reinvestment ratio (CRR_{it}) were 13.639%, -209.156%, and -7.009%, respectively. Only the average CRR_{it} was negative before COVID-19 (-13.400%), but it became positive during the COVID-19 pandemic (2.706%), which changed to a greater extent. Finally, the means of CFR_{it} and CRR_{it} during the postpandemic period decreased, whereas $CFAR_{it}$ increased and turned from negative to positive, and the directions of the changes in these indicators were inconsistent.

Regarding the firms' basic operational status, the means and standard deviations for the entire observation period were as follows: operating revenue, 1,259,918.0 and 2,592,412.1 thousand NTD; revenue growth rate, 29.546 and 171.493%; book value per share, 19.001 and 16.173 NTD/share; number of employees, 200.716 and 274.214 persons; and paid-in capital, 604,994.45 and 677,620.04 thousand NTD. The firm's average annual operating income and revenue growth rate were approximately NT\$1.26 billion and 19%, respectively, with an average of 200 sales staff. During the COVID-19 pandemic, the revenue growth rate declined significantly from 38.637% to 12.386%, indicating a slowdown in growth. In contrast, the other four indicators showed minimal variation between the prepandemic and pandemic periods. These findings diverge from the broader economic downturn reported by Kantor and Kubiczek (2021), possibly due to effective government interventions, including relief and revitalization measures. Postpandemic averages were comparable to prepandemic levels, with operating income, employee numbers, and paid-in capital even exceeding prepandemic figures, suggesting a gradual recovery in operational performance.

This study revealed that these C&CI firms already have stocks listed on the securities market, making it easier for them to obtain financing from financial institutions or raise funds through the issuance of securities (this case tends to be consistent with the first situation mentioned by Ellul et al. (2020)). Therefore, during the COVID-19 pandemic, the financial structure and basic operating conditions of C&CI firms have largely remained unchanged.

3.2 Test for equality of means

Table 3 presents the results of testing for the equality of means of financial indicators and basic operating status during the pandemic vs. pre-COVID-19 periods.

Table 3. Tests for the equality of means of indicators during the pandemic vs. pre-COVID-19 periods.

Indicator	Mean Difference (Pandemic – Pre)	Equality of Means		Equality of Variances
		t test (p value)	Satterthwaite-Welch t test* (p value)	Levene's test (p value)
1.1 DR_{it}	0.897	0.722	0.719	0.931
1.2 $FATAR_{it}$	-1.578	0.430	0.425	0.600
1.3 $LFFAR_{it}$	9688.656	0.011	0.037	0.000
2.1 $WCTAR_{it}$	-0.465	0.904	0.901	0.575
2.2 CR_{it}	-22.044	0.513	0.486	0.161
2.3 QR_{it}	-3.777	0.896	0.890	0.363
2.4 $CCLR_{it}$	9.226	0.001	0.001	0.577
2.5 TIE_{it}	608.520	0.481	0.531	0.009
3.1 RT_{it}	2.241	0.336	0.361	0.146
3.2 IT_{it}	-1004.027	0.605	0.548	0.327
3.3 $FATR_{it}$	25.614	0.037	0.054	0.002
3.4 ATR_{it}	-0.226	0.001	0.000	0.012
4.1 ROA_{it}	-0.786	0.714	0.715	0.495
4.2 ROE_{it}	-12.763	0.040	0.030	0.352
4.3 PM_{it}	-476.165	0.068	0.153	0.000
4.4 OIM_{it}	-369.403	0.074	0.163	0.001
4.5 EPS_{it}	0.412	0.628	0.661	0.077
5.1 CFR_{it}	3.210	0.728	0.718	0.651

5.2 CFAR _{it}	10.054	0.971	0.971	0.936
5.3 CRR _{it}	16.105	0.444	0.329	0.213
Operating Revenue	-25843.174	0.931	0.931	0.754
Revenue Growth Rate	-26.251	0.186	0.129	0.273
Book Value Per Share	-0.083	0.965	0.966	0.588
Number of Employees	-1.712	0.957	0.957	0.873
Paid in Capital	-9267.265	0.906	0.906	0.890

Note: * indicates that the test allows for unequal cell variances.

Source: Own elaboration.

The first column shows the difference between the average indicators during the COVID-19 pandemic and the average indicators during the pre-COVID-19 period. The p values of the second and third columns are the t test and Satterthwaite–Welch t test, respectively, and the Satterthwaite–Welch t test is the result of the test performed under conditions that allow for unequal cell variances, which is the test of the mean difference. The fourth column shows the results of Levene's test for equality of variances. At the 5% significance level, the following conclusions can be drawn:

Financial structure: The mean difference in the ratio of long-term funds to fixed assets (LFFAR_{it}) was 9688.656%, and the p value was $0.037 < 0.05$ for the Satterthwaite–Welch t test, with a p value = $0.000 < 0.05$ for Levene's test. The results confirmed a significant difference between the means of these indicators in the pandemic and pre-COVID-19 periods, indicating that the means increased substantially during the pandemic.

Solvency: The mean difference in the cash-to-current liabilities ratio (CCLR_{it}) was 9.226%, and the p value was $0.001 < 0.05$ for the t test under the condition of a p value = $0.577 > 0.05$ for Levene's test. It was confirmed that there was a significant difference between the means during the pandemic and pre-COVID-19 periods and that the mean during the pandemic was significantly greater than that during the pre-COVID-19 periods. Possible reasons and industry players increased the company's cash and cash equivalents offered during the epidemic (the average during the pre-COVID-19 period was 437,253.1 NTD thousand; the average value during the pandemic period was 628,291.0 NTD thousand).

Operating ability: The mean difference in the asset turnover ratio (ATR_{it}) was -0.226%, and the p value of the Satterthwaite–Welch t test was $0.000 < 0.05$ when the p value of Levene's test was $0.012 < 0.05$. As a result, the mean will be significantly lower during the pandemic.

Profitability: The mean difference in the ROE (ROE_{it}) was -12.763%, and the p value of the t test was $0.040 < 0.05$ when the p value of Levene's test was $0.352 > 0.05$. The mean was confirmed to be significantly smaller (decrease) during the pandemic.

Cash flows and basic operating status: There is no evidence to support the means of cash flows and basic operating status, indicating that there is a significant difference between the COVID-19 pandemic and pre-pandemic periods. Therefore, it is not possible to support the fact that the COVID-19 pandemic has had a significant effect on the cash flow and basic operating status of C&CI firms.

On the basis of the above results, C&CIs, when faced with major infectious disease events, experienced significant changes in a few financial indicators due to numerous government relief policies and the advantages of listed companies in issuing securities and obtaining financing from financial institutions. The firms' financial condition and basic operating status did not undergo comprehensive changes in the face of the significant impact of major events. There are even signs that the firms were more capable of resisting the impact of major crisis events and making financial adjustments (e.g., financial structure (LFFAR_{it}) and solvency (CCLR_{it})).

3.3 Tests for Equality of Means in Digital vs. Nondigital Game Companies

DT has been proven to be important for financial performance (Stefanovic et al., 2021; Kantor & Kubiczek, 2021; Zhang et al., 2022), and it has significant positive effects (Mahssouni et al., 2023). Similarly, the impact of innovative practices on financial performance is also significant (Kurniawan et al., 2023). Digital gaming is a cross-cutting industry that blends various elements of technology,

entertainment, culture, and social networking. This industry accounts for more than 40% of the C&CIs on Taiwan's stock market, and under the many control measures that restrict people's work, school, and public living spaces and places during the epidemic, people's time in family life has increased significantly, and it is expected to increase the time spent on online leisure, so it is generally expected to have a positive impact on the digital game industry. Therefore, this study further divides the sample firms into digital game industries (groups) that focus on digital content, including software and related hardware. In addition, after digital game firms are excluded, the remaining C&CI firms are classified into nondigital game groups, which tend to be negative or neutral because of the impact of the epidemic. This study categorises firms into digital game and nondigital game groups to examine the impact of the COVID-19 pandemic. Table 4 presents tests for the equality of means of financial indicators and basic operating status during the COVID-19 pandemic compared to pre-COVID-19 periods, based on digital versus nondigital game groups.

Table 4. Tests for the equality of means on digital vs. nondigital game groups.

Indicator	Digital Game Group				Non-Digital Game Group			
	Mean Difference	t test p value	Satt.-Welc.* p value	Leve. test p value	Mean Difference	t test p value	Satt.-Welc.* p value	Leve. test p value
1.1 DR _{it}	-5.302	0.137	0.100	0.057	7.773	0.028	0.042	0.035
1.2 FATAR _{it}	-2.685	0.100	0.079	0.009	-0.419	0.908	0.907	0.916
1.3 LFFAR _{it}	3486.111	0.200	0.168	0.165	16552.772	0.026	0.079	0.000
2.1 WCTAR _{it}	4.864	0.392	0.368	0.482	-6.342	0.210	0.212	0.449
2.2 CR _{it}	22.079	0.467	0.476	0.771	-71.380	0.254	0.213	0.122
2.3 QR _{it}	22.904	0.353	0.353	0.975	-33.569	0.540	0.509	0.258
2.4 CCLR _{it}	10.670	0.001	0.001	1.000	7.666	0.096	0.100	0.664
2.5 TIE _{it}	2531.678	0.093	0.121	0.004	-1532.945	0.053	0.107	0.000
3.1 RT _{it}	1.559	0.096	0.127	0.035	2.941	0.536	0.556	0.213
3.2 IT _{it}	-1869.435	0.612	0.555	0.346	-20.190	0.687	0.639	0.513
3.3 FATR _{it}	10.959	0.501	0.500	0.562	41.997	0.024	0.053	0.000
3.4 ATR _{it}	-0.259	0.011	0.006	0.015	-0.186	0.002	0.001	0.024
4.1 ROA _{it}	4.210	0.186	0.180	0.563	-6.342	0.024	0.029	0.091
4.2 ROE _{it}	-6.267	0.537	0.482	0.513	-19.976	0.003	0.009	0.002
4.3 PM _{it}	10.218	0.103	0.124	0.776	-1023.672	0.062	0.148	0.000
4.4 OIM _{it}	-12.593	0.217	0.309	0.022	-771.120	0.077	0.171	0.001
4.5 EPS _{it}	1.921	0.196	0.247	0.120	-1.256	0.073	0.078	0.332
5.1 CFR _{it}	8.700	0.391	0.400	0.367	-2.889	0.856	0.845	0.266
5.2 CFAR _{it}	-0.165	0.999	0.999	0.599	65.817	0.908	0.909	0.831
5.3 CRR _{it}	31.102	0.444	0.325	0.189	-0.071	0.985	0.985	0.511
Operating Revenue	8184.000	0.988	0.988	0.617	-67505.461	0.686	0.688	0.902
Revenue Growth Rate	-36.517	0.257	0.175	0.220	-14.758	0.500	0.486	0.984
Book Value Per Share	2.053	0.525	0.549	0.549	-2.411	0.101	0.098	0.974
Number of Employees	-1.139	0.977	0.977	0.927	-2.164	0.966	0.966	0.890
Paid in Capital	-8375.432	0.939	0.939	0.949	-10272.751	0.929	0.928	0.898

Note: * indicates that the test allows for unequal cell variances.

Source: Own elaboration.

The left/right halves of Table 4 show the mean differences for the digital/nondigital game group and the results of the t tests and Satterthwaite-Welch t tests of the equality of means and Levene's tests for the equality of variances. Judging from the results of the indicator testing of the five categories of major financial indicators:

Financial structure: The mean difference in the debt ratio (DR_{it}) in the digital/nondigital game group was -5.302%/7.773%, indicating that the firms in these two groups changed in different

directions during the pandemic. Under the condition of $p \text{ value} = 0.035 < 0.05$ for the t test of Levene's tests of the nondigital game group, the p value of the Satterthwaite–Welch t test was $0.042 < 0.05$, thus confirming that the debt ratio (DR_{it}) of the nondigital game group was significantly greater during the COVID-19 pandemic than during the pre-COVID-19 period. The mean difference in the ratio of fixed assets to total assets ($FATAR_{it}$) in the digital/nondigital game groups was $-2.685\%/-0.419\%$, indicating that the means for both groups decreased during the COVID-19 pandemic; however, the differences were not statistically significant. The mean difference in the long-term funds to fixed assets ratio ($LFFAR_{it}$) in the digital/nondigital game group was $3486.111\%/16552.772\%$, indicating that the mean of both groups increased during the COVID-19 pandemic, but the difference was not statistically significant. The above results provide evidence that the COVID-19 pandemic significantly increased financial default risk (as measured by the debt ratio) for nondigital game groups; however, there is no evidence that the pandemic had a significant impact on the financial structure of digital game groups.

Solvency: The mean differences in the working capital-to-total assets ratio ($WCTAR_{it}$), current ratio (CR_{it}), quick ratio (QR_{it}) and number of times interest earned (TIE_{it}) in the digital/nondigital game group were $4.864\%/-6.342\%$, $22.079\%/-71.380\%$, $22.079\%/-33.569\%$ and $2531.678 \text{ times}/-1532.9455 \text{ times}$, respectively, indicating that the direction of change in these indicators between the two types of firms during the epidemic was inconsistent (up/down). Second, the mean difference in the cash-to-current liabilities ratio ($CCLR_{it}$) in the digital/nondigital game group was $10.670\%/7.666\%$, the p value of Levene's test was $1.000/0.664 > 0.05$, and the p value of the t test was $0.001 < 0.05/0.096 > 0.05$. Therefore, the mean cash-to-current liabilities ratio ($CCLR_{it}$) in the two groups during the COVID-19 pandemic period will be significantly higher, which may be related to the increase in the firm's cash ratio (amount) in response to the epidemic's impact. Among these groups, the digital game groups yielded particularly significant results, suggesting that digital game groups may have been better positioned to manage their cash flow during the COVID-19 pandemic than nondigital game groups were. Taken together, there is evidence to support some significant impacts (changes) of the COVID-19 pandemic on the solvency of digital game groups. In general, the solvency of the digital game group tends to be positive, especially in terms of the cash-to-current liabilities ratio, which has a significant positive effect (increase). However, for the nondigital game group, there was a negative response in the working capital-to-total assets ratio ($WCTAR_{it}$), current ratio (CR_{it}), quick ratio (QR_{it}), and number of interest earned (TIE_{it}), but for the cash-to-current liabilities ratio ($CCLR_{it}$), there was a significant positive reaction. However, the nondigital game group showed a negative reaction, but it was not statistically significant.

Operating ability: The mean differences in inventory turnover (IT_{it}) and the asset turnover ratio (ATR_{it}) in the digital/nondigital game group were negative: $-1869.435 \text{ times}/-20.190 \text{ times}$ and $-0.259\%/-0.186\%$, respectively. The asset turnover ratio ($ATR_{it}ATR$) of the digital/nondigital game groups was $p = 0.015/0.024 < 0.05$ for Levene's test and $p = 0.006/0.001 < 0.05$ for the Satterthwaite–Welch t-test, indicating a significantly smaller (decrease) mean during the COVID-19 pandemic. Therefore, only one indicator yielded significant results, supporting the impacts of the epidemic on operating ability.

Profitability: The mean difference in ROA (ROA_{it}) was -6.342% , where the p value for the t test was $0.024 < 0.05$ ($p \text{ value} = 0.091 > 0.05$ for Levene's test), and the mean difference in ROE (ROE_{it}) was -19.976% , where the p value for the Satterthwaite–Welch t test was $0.009 < 0.05$ ($p \text{ value} = 0.091 > 0.05$ for Levene's test) in the nondigital game group. This confirms that the means of these two measures of profitability decreased significantly during the COVID-19 pandemic (negative effect). In addition, the mean differences in ROA (ROA_{it}), profit margin (PM_{it}), and EPS (EPS_{it}) in the digital game group were positive, but it cannot be confirmed that there was a significant difference between the COVID-19 pandemic period and the pre-COVID-19 period. The results confirmed that the pandemic had a significant negative effect on two (partial) indicators of profitability for the

nondigital game group, whereas for the digital game group, although the mean differences for the three indicators were positive, none of them reached statistical significance.

Cash flows: There was no evidence that the pandemic would significantly change (impact) the cash flows of the digital/nondigital game group, as it was not significant in the measurement of the equality of means for all three indicators of cash flows.

Finally, the indicators of the basic operating status are included. The operating revenue of digital/nondigital game groups during the COVID-19 pandemic has increased/decreased, the revenue growth rate has decreased/decreased, the book value per share has increased/decreased, the number of employees has slightly decreased/slightly decreased, and the paid-in capital has increased/decreased. Comparing the results of the two groups, there is a positive mean difference in the operating revenue of the digital game group, although no significant results are achieved, which tends to be a positive result for the digital game group during the pandemic.

These results are based on the fact that C&CIs have greater access to financing from financial institutions and by issuing securities on the securities market. This confirms that these firms experience some differences in their financial performance compared with their peers following major events. Some confirm that the digital gaming industry performed relatively better than did the nondigital gaming industry during the COVID-19 pandemic in terms of financial structure (DR_{it}), solvency ($CCLR_{it}$), and profitability (ROA_{it} and ROE_{it}). These financial advantages provide evidence that digital technology-focused C&CIs (digital gaming) outperform their peers during similar major events.

3.4 Tests for the Same Median and Distribution in Two Groups

Tables 3 and 4 present the results of statistical tests for the equality of means between groups (pandemic period and pre-COVID-19 period) for the C&CI group, the digital game group, and the nondigital game group. These tests were used to determine whether the means of the two independent groups were significantly different. To further investigate whether the COVID-19 pandemic had a significant effect on the median and distribution of these two independent groups, this study used the nonparametric Mann-Whitney test to compare the medians of the two groups. Additionally, the two-sample Kolmogorov-Smirnov test was used to determine whether the distributions of the financial indicators were the same in the pre-COVID-19 and pandemic periods. These tests provided further insights into the impact of the COVID-19 pandemic on other statistical characteristics of the indicators.

Table 5 presents the results of the Mann-Whitney tests and Kolmogorov-Smirnov tests for the C&CI, digital game, and non-digital game groups. The Mann-Whitney test assumes that the null hypothesis is that the medians of two independent groups (pandemic period and pre-COVID-19 period) are the same, whereas the Kolmogorov-Smirnov test assumes that the distributions of the two independent groups are the same. In the Mann-Whitney tests, for C&CI, $CCLR_{it}$ (p value < 0.001) and (p value = 0.001) was significantly different, which is consistent with the results in Table 3 and indicates that the medians of these two indicators differed between the pandemic and pre-COVID-19 periods. Similarly, the p value of the revenue growth rate (p value = 0.021 < 0.05) also supported a significant difference in the median between the two periods. For the digital game group, $CCLR_{it}$ (p value = 0.026 < 0.05) and ATR_{it} (p value = 0.042 < 0.05) were significantly different, which is consistent with Table 4. Additionally, $FATAR_{it}$ (p value = 0.001 < 0.05) and $LFFAR_{it}$ (p value = 0.020 < 0.05) also significantly differed, indicating that the medians of these four indicators differed between the two periods. For the nondigital game group, ATR_{it} (p value = 0.002 < 0.05), ROA_{it} (p value = 0.017 < 0.05), and ROE_{it} (p value = 0.007 < 0.05) were significantly different, which is consistent with Table 4. Additionally, EPS_{it} (p value = 0.007 < 0.05) was significantly different, indicating that the medians of these four indicators differed between the pandemic and pre-COVID-19 periods.

Finally, the results of the C&CI Kolmogorov-Smirnov test revealed that $CCLR_{it}$ and ATR_{it} were statistically significant, which is consistent with the results in Table 3 and the results of the

Mann-Whitney tests. Similarly, $FATAR_{it}$, OIM_{it} , and $CFAR_{it}$ were significant, suggesting that the distributions of these five indicators differed between the pandemic period and the pre-COVID-19 period.

Table 5. Results of the Mann-Whitney and Kolmogorov-Smirnov tests.

Indicator	C&CI				Digital Game Group				Non-Digital Game Group			
	1		2		1		2		1		2	
	z stat.	p value	z stat.	p value	z stat.	p value	z stat.	p value	z stat.	p value	z stat.	p value
1.1DR _{it}	-0.611	0.541	1.204	0.110	-0.651	0.515	0.873	0.431	-1.685	0.092	0.894	0.401
1.2FATAR _{it}	-1.962	0.050	1.486	0.024	-2.231	0.026	1.339	0.055	-0.670	0.503	1.095	0.182
1.3LFFAR _{it}	-1.761	0.078	1.326	0.059	-2.324	0.020	1.279	0.076	-0.051	0.960	0.808	0.532
2.1WCTAR _{it}	-0.306	0.760	0.807	0.533	-0.657	0.511	0.626	0.828	-0.859	0.390	1.082	0.193
2.2CR _{it}	-0.176	0.860	0.796	0.551	-0.478	0.633	0.742	0.641	-0.715	0.475	0.825	0.505
2.3QR _{it}	-0.576	0.565	0.807	0.533	-0.987	0.324	0.808	0.531	-0.082	0.935	0.766	0.601
2.4CCLR _{it}	-3.564	0.000	2.072	0.000	-3.343	0.001	2.054	0.000	-1.855	0.064	1.163	0.134
2.5TIE _{it}	-0.272	0.785	0.947	0.331	-1.151	0.250	1.046	0.224	-1.818	0.069	1.379	0.045
3.1RT _{it}	-0.940	0.347	0.897	0.396	-1.337	0.181	0.946	0.333	-0.020	0.984	0.459	0.984
3.2IT _{it}	-1.073	0.283	0.779	0.579	-0.755	0.450	0.761	0.609	-0.595	0.552	0.777	0.581
3.3FATR _{it}	-1.139	0.255	1.219	0.102	-1.171	0.241	0.892	0.404	-0.123	0.902	0.860	0.450
3.4ATR _{it}	-3.381	0.001	1.561	0.015	-2.029	0.042	1.208	0.108	-3.050	0.002	1.441	0.032
4.1ROA _{it}	-0.830	0.406	1.108	0.172	-1.006	0.315	0.781	0.575	-2.381	0.017	1.620	0.010
4.2ROE _{it}	-1.389	0.165	1.177	0.125	-0.588	0.556	0.648	0.795	-2.678	0.007	1.862	0.002
4.3PM _{it}	-0.343	0.732	1.104	0.175	-1.606	0.108	1.091	0.184	-1.726	0.084	1.732	0.005
4.4OIM _{it}	-1.297	0.195	1.575	0.014	-0.024	0.981	0.707	0.700	-1.591	0.112	1.732	0.005
4.5EPS _{it}	-1.229	0.219	1.076	0.197	-0.708	0.479	0.978	0.294	-2.676	0.007	1.833	0.002
5.1CFR _{it}	-0.436	0.663	0.546	0.927	-0.783	0.434	0.843	0.476	-0.145	0.885	0.596	0.869
5.2CFAR _{it}	-1.647	0.100	2.121	0.000	-1.509	0.131	1.564	0.015	-0.997	0.319	1.482	0.025
5.3CRR _{it}	-0.203	0.839	0.548	0.925	-0.418	0.676	0.694	0.721	-0.287	0.774	0.536	0.936
Operating Revenue	-1.342	0.179	1.015	0.254	-0.975	0.329	0.649	0.794	-1.035	0.301	0.852	0.462
Revenue Growth Rate	-2.309	0.021	1.307	0.066	-1.812	0.070	0.913	0.375	-1.409	0.159	1.028	0.241
Book Value Per Share	-0.743	0.458	0.884	0.415	-0.260	0.795	0.653	0.787	-1.394	0.163	1.347	0.053
Number of Employees	-0.109	0.913	0.133	1.000	-0.040	0.968	0.064	1.000	-0.141	0.888	0.132	1.000
Paid in Capital	-0.147	0.883	0.127	1.000	-0.130	0.897	0.092	1.000	-0.141	0.888	0.132	1.000

Note: 1 - Mann-Whitney test (Null hypothesis : the medians were equal across both periods); 2 - Kolmogorov-Smirnov test (Null hypothesis : the distributions were equal across both periods).

Source: Own elaboration.

For the digital game group, $CCLR_{it}$ was significant, which is consistent with the results of Table 4 and the Mann-Whitney tests, and $CFAR_{it}$ (p value = $0.015 < 0.05$) was significant, indicating that only two indicators showed significant differences in distribution between the two periods and thus had a limited impact. For the nondigital game group, ATR_{it} , ROA_{it} , and ROE_{it} were significant, which is consistent with Table 4 and the results of the Mann-Whitney tests. Additionally, TIE_{it} , PM_{it} , OIM_{it} , EPS_{it} , and $CFAR_{it}$ were significant, suggesting that the distributions of these eight indicators differed between the pandemic and pre-COVID-19 periods and thus had broader impacts.

Conclusions

This study explored the impact of major infectious disease events on C&CI firms in Taiwan's stock market and focused on the changes in financial statement data and basic operating status disclosed by companies during the COVID-19 pandemic (2020--2022). Because this annual statement is regulated by the relevant laws and regulations of the local government and the financial information of the firm issued by a registered and qualified accountant, it has considerable credibility. In addition, the C&CI firms in the Taiwan stock market are based mainly on digital

content and emphasize technology, especially in the field of digital games. The impact of COVID-19 was analyzed by testing the equality of means during the pre-COVID-19 (2015--2019) and COVID-19 pandemics from the five categories of major financial indicators of individual firms, including financial structure, solvency, operating ability, profitability, and cash flows, as well as basic operating status. The data from the postpandemic period (2023) were compared to observe the postpandemic industry, which showed recovery. Second, according to the characteristics of the industrial structure and the expected impact of the epidemic on the DGI, the sample firms were divided into digital game groups and nondigital game groups for group testing to understand the actual results of the impact of the epidemic on the digital game industry and the differences between the groups. The results of this study can be used as a reference for the financial management of C&CIs in dealing with similar major events in the future and as a supporting document for the industry to examine the advantages of the DGI in the financial performance of major infectious diseases.

Through empirical evidence, the following conclusions were drawn: 1) Financial structure: only the mean and standard deviation (risk) of the ratio of long-term funds to fixed assets increased during the COVID-19 pandemic, whereas the mean did not decrease, but the standard deviation decreased during the postpandemic period. The rest of the indicators did not change much, and the impact of the epidemic was limited. It was confirmed that the mean ratio of long-term funds to fixed assets during the COVID-19 pandemic was significantly greater than that during the pre-COVID-19 period. During the COVID-19 pandemic, the debt ratio of the nondigital game group was significantly greater than that of the digital game group, whereas no significant differences were observed in the financial structure indicators of the digital game group. There was evidence suggesting that the digital game group had an advantage in financial structure over the nondigital game group. 2) Solvency: The average cash-to-current liabilities ratio of the overall industry increased significantly during the COVID-19 pandemic. The solvency indicators in the postpandemic period were all greater than they were before the COVID-19 pandemic, indicating their strategies to improve their solvency to cope with the impact of similar emergencies. The cash-to-current liabilities ratio for the digital game group was significantly greater than that for the pre-COVID-19 group, indicating that the digital game group significantly increased its cash and cash equivalents during the COVID-19 pandemic as a financial strategy to cope with the uncertainties and risks associated with the pandemic. 3) Operating ability: The direction of the impact of industry overall on the indicators of operating ability during the COVID-19 pandemic has been inconsistent. During the COVID-19 pandemic, asset turnover rates were significantly lower, and this result was consistent across both the digital gaming and nondigital gaming groups. 4) Profitability: Only the EPS of the overall industry had a positive mean, and the other four indicators had negative averages, indicating that the profits did not simply come from the operation of the business and may have contributed from outside the business. Only EPS increased during the COVID-19 pandemic, whereas the rest declined. Since the pandemic, profitability has yet to recover to pre-COVID-19 levels and continues to decline. It has been confirmed that ROE will be significantly lower than pre-COVID-19 levels during the COVID-19 pandemic. Second, the ROA and ROE of the nondigital game group were significantly lower than those of the pre-COVID-19 group during the COVID-19 pandemic, whereas the digital game group did not exhibit a significant change in profitability during the same period. The decrease in profitability during the pandemic period was largely due to the nondigital game group. Finally, the profitability of digital game groups did not change significantly during the COVID-19 pandemic, which was contrary to market expectations. 5) Cash flows: The cash reinvestment ratio of the industry as a whole changed to a greater extent, with a negative mean during the pre-COVID-19 pandemic but a positive mean during the COVID-19 pandemic. There was no evidence to support a significant change (difference) in cash flows during the COVID-19 pandemic, and the results were approximately the same for both the digital game groups and the nondigital game groups. In terms of basic operating status, the revenue growth rate of the overall

industry decreased from 38.637% during the pre-COVID-19 pandemic to 12.386% during the COVID-19 pandemic. The means of the other indicators did not change much during the COVID-19 pandemic. Second, the basic situation of postpandemic operations gradually returned to the pre-COVID-19 level, and some indicators even exceeded the average level of the past. Finally, there was no evidence to support a significant change in the fundamentals of a firm's operations during the COVID-19 pandemic, and consistent results were observed for both digital game groups and non-digital game groups.

The limitations of this study were as follows: 1) Limitations of the sample firms: This study used the annual financial statements of the firms listed on the Taiwan stock market as the analysis data, and these firms had a certain degree of credibility and credibility due to the supervision of qualified accountants and government regulations; however, the sample firms belong to the local peers who prefer to have scale, so they cannot be discussed for some small-scale or sole proprietorship cultural entrepreneurs. In addition, C&CIs' stocks listed on the Taiwan stock market had a biased industrial structure toward digital technology and creativity, raising doubts about the underrepresentation of cultural companies. 2) The data source for this study was a paid database of TEJD. Although this professional financial database was compiled from statistics based on the Taiwan Securities and Financial Markets and the research data had considerable credibility and accuracy, bias may still exist and was therefore considered an uncontrollable condition. 3) Limitations of the empirical methods: In this study, the financial data of 40 firms for 9 years were used to test the individual study variables. The important priorities of the changes in financial indicators caused by the epidemic should be further explored in the future as a reference for management decision-making. 4) In this study, the study variables (indicators) were classified purely according to the pre-COVID-19 and COVID-19 pandemic periods for empirical testing, without considering policy or other potential external factors. In particular, the impact and benefits of some relief policies and revitalization programs implemented by the government on local C&CIs have not been considered and excluded in the empirical process, and future follow-up studies should further consider the impact of policy benefits.

Author Contributions: Conceptualization, L.L. and Y.S.L.; methodology, Y.S.L.; software, Y.S.L.; validation, L.L. and Y.S.L.; formal analysis, Y.S.L.; investigation, Y.S.L.; resources, L.L.; data curation, Y.S.L.; writing-original draft preparation, Y.S.L.; writing-review and editing, Y.S.L.; visualization, L.L. and Y.S.L.; supervision, L.L.; project administration, L.L. All authors have read and agreed to the published version of the manuscript

Funding: This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Data Availability Statement: The data used in the study were obtained from TEJD. Datasets generated from this study will be available from the corresponding author upon reasonable request.

Conflicts of Interest: The authors affirm no conflict of interest.

Reference

1. Achim, M. V., Safta, I. L., Văidean, V. L., Mureșan, G. M., & Nicolae Sorin Borlea, N. S. (2022). The impact of COVID-19 on financial management: evidence from Romania. *Economic Research-Ekonomska Istraživanja*, 35(1), 1807–1832. <https://doi.org/10.1080/1331677X.2021.1922090>.
2. Amankwah-Amoah, J., Khan, Z., & Wood, G. (2021). COVID-19 and business failures: the paradoxes of experience, scale, and scope for theory and practice. *European Management Journal*, 39(2), 179–184. <https://doi.org/10.1016/j.emj.2020.09.002>.
3. Ardito, L. (2023). The influence of firm digitalization on sustainable innovation performance and the moderating role of corporate sustainability practices: an empirical investigation. *Business Strategy and the Environment*, 32(8), 5252–5272. <https://doi.org/10.1002/bse.3415>.

4. Atayah, O. F., Dhiaf, M. M., Najaf, K., & Frederico, G. F. (2022). Impact of COVID-19 on financial performance of logistics firms: evidence from G-20 countries. *Journal of Global Operations and Strategic Sourcing*, 15(2), 172–196. <https://doi.org/10.1108/JGOSS-03-2021-0028>.
5. Bakhshi, H., Di Novo, S., & Fazio, G. (2023). The “Great Lockdown” and cultural consumption in the UK. *Journal of Cultural Economics*, 47, 555–587. <https://doi.org/10.1007/s10824-022-09463-6>.
6. Che Arshad, N., & Irijanto, T. T. (2023). The creative industries effects on economic performance in the time of pandemic. *International Journal of Ethics and Systems*, 39(3), 557–575. <https://doi.org/10.1108/IJOES-10-2021-0199>.
7. Chen, C. W., Sutton, N. K., Yi, B., & Zheng, Q. (2023). The connection between gender diversity and firm performance: evidence from Taiwan. *International Review of Financial Analysis*, 89, Article 102763. <https://doi.org/10.1016/j.irfa.2023.102763>.
8. Chen, Y. C., & Liu, J. T. (2022). Seasoned equity offerings, return of capital and agency problem: empirical evidence from Taiwan. *Asia Pacific Management Review*, 27(2), 92–105. <https://doi.org/10.1016/j.apmr.2021.05.006>.
9. Chen, Y. C., & Liu, Y. S. (2023). Market efficiency and stock investment loss aversion guide during COVID-19 pandemic events: the case for applying data mining. *SAGE Open*, 13(4). <https://doi.org/10.1177/21582440231215956>.
10. Cho, S. J., Chung, C. Y., & Young, J. (2019). Study on the relationship between CSR and financial performance. *Sustainability*, 11(2), Article 343. <https://doi.org/10.3390/su11020343>.
11. Cunningham, S., McCutcheon, M., Hearn, G., & Ryan, M. D. (2021). ‘Demand’ for culture and ‘allied’ industries: policy insights from multi-site creative economy research. *International Journal of Cultural Policy*, 27(6), 768–781. <https://doi.org/10.1080/10286632.2020.1849168>.
12. Ding, Y. J., Guo, J. L., & Tsai, C. W. (2025). The influence of ESG performance on credit risk and financial distress: an empirical study on Taiwan corporate sustainability. *Applied Economics*, 57(12), 1351–1367. <https://doi.org/10.1080/00036846.2024.2312262>.
13. Dörr, J. O., Licht, G., & Murmann, S. (2022). Small firms and the COVID-19 insolvency gap. *Small Business Economics*, 58, 887–917. <https://doi.org/10.1007/s11187-021-00514-4>.
14. Dümcke, C. (2021). Five months under COVID-19 in the cultural sector: a German perspective. *Cultural Trends*, 30(1), 19–27. <https://doi.org/10.1080/09548963.2020.1854036>.
15. Ekinci, R., & Poyraz, G. (2019). The effect of credit risk on financial performance of deposit banks in Turkey. *Procedia computer science*, 158, 979–987. <https://doi.org/10.1016/j.procs.2019.09.139>.
16. Ellul, A., Erel, I., & Rajan, U. (2020). The COVID-19 pandemic crisis and corporate finance. *Review of Corporate Finance Studies*, 9(3), 421–429. <https://doi.org/10.1093/rcfs/cfaa016>.
17. Elnahass, M., Trinh, V. Q., & Li, T. (2021). Global banking stability in the shadow of Covid-19 outbreak. *Journal of International Financial Markets, Institutions and Money*, 72, Article 101322. <https://doi.org/10.1016/j.intfin.2021.101322>.
18. Escalona-Orcao, A., Barrado-Timón, D. A., Escolano-Utrilla, S., Sánchez-Valverde, B., Navarro-Pérez, M., Pinillos-García, M., & Sáez-Pérez, L. A. (2021). Cultural and creative ecosystems in medium-sized cities: evolution in times of economic crisis and pandemic. *Sustainability*, 13(1), Article 49. <https://doi.org/10.3390/su13010049>.
19. Gao, Y., Turkina, E., & Van Assche, A. (2024). The nexus between the cultural and creative industries and the sustainable development goals: a network perspective. *Regional Studies*, 58(4), 841–859. <https://doi.org/10.1080/00343404.2023.2252474>.
20. Grewal, J., & Serafeim, G. (2020). Research on corporate sustainability: review and directions for future research. *Foundations and Trends® in Accounting*, 14(2), 73–127. <http://dx.doi.org/10.1561/14000000061>.

21. Gustafsson, C., & Lazzaro, E. (2021). The innovative response of cultural and creative industries to major European societal challenges: toward a knowledge and competence base. *Sustainability*, 13(23), Article 13267. <https://doi.org/10.3390/su132313267>.
22. Handke, C., & Dalla Chiesa, C. (2022). The art of crowdfunding arts and innovation: the cultural economic perspective. *Journal of Cultural Economics*, 46, 249–284. <https://doi.org/10.1007/s10824-022-09444-9>.
23. Hosseini, E., & Rajabipoor Meybodi, A. (2023). Proposing a model for sustainable development of creative industries based on digital transformation. *Sustainability*, 15(14), Article 11451. <https://doi.org/10.3390/su151411451>.
24. Iqbal, S., Nawaz, A., & Ehsan, S. (2019). Financial performance and corporate governance in microfinance: evidence from Asia. *Journal of Asian Economics*, 60, 1–13. <https://doi.org/10.1016/j.asieco.2018.10.002>.
25. Jeannotte, M. S. (2021). When the gigs are gone: valuing arts, culture and media in the COVID-19 pandemic. *Social Sciences & Humanities Open*, 3(1), Article 100097. <https://doi.org/10.1016/j.ssaho.2020.100097>.
26. Joffe, A. (2021). Covid-19 and the African cultural economy: an opportunity to reimagine and reinvigorate? *Cultural Trends*, 30(1), 28–39. <https://doi.org/10.1080/09548963.2020.1857211>.
27. Kantor, A., & Kubiczek, J. (2021). Polish culture in the face of the COVID-19 pandemic crisis. *Journal of Risk and Financial Management*, 14(4), Article 181. <https://doi.org/10.3390/jrfm14040181>.
28. Karim, S., Iqbal, M. S., Ahmad, N. et al. (2023). Gene expression study of breast cancer using Welch Satterthwaite t-test, Kaplan-Meier estimator plot and Huber loss robust regression model. *Journal of King Saud University - Science*, 35(1), Article 102447. <https://doi.org/10.1016/j.jksus.2022.102447>.
29. Kaźmierska-Jóźwiak, B., Sekuła, P., & Socha, B. (2021). Analysis of the effects of COVID-19 on companies listed on the Warsaw Stock Exchange. *Forum Scientiae Oeconomia*, 9(4), 99–116. https://doi.org/10.23762/FSO_VOL9_NO4_5.
30. Khlystova, O., Kalyuzhnova, Y., & Belitski, M. (2022). The impact of the COVID-19 pandemic on the creative industries: a literature review and future research agenda. *Journal of business research*, 139, 1192–1210. <https://doi.org/10.1016/j.jbusres.2021.09.062>.
31. Khlystova, O., & Kalyuzhnova, Y. (2023). The impact of the creative industries and digitalization on regional resilience and productive entrepreneurship. *The Journal of Technology Transfer*, 48(5), 1654–1695. <https://doi.org/10.1007/s10961-023-10020-2>.
32. Konhäuser, P., Semmerau, S. M., & Grunert, M. (2021). Microtransactions in games – an analysis of a crowdfunding perspective. *Forum Scientiae Oeconomia*, 9(4), 31–58. https://doi.org/10.23762/FSO_VOL9_NO4_2.
33. Kücher, A., Mayr, S., Mitter, C., Duller, C., & Feldbauer-Durstmüller, B. (2020). Firm age dynamics and causes of corporate bankruptcy: age dependent explanations for business failure. *Review of Managerial Science*, 14(3), 633–661. <https://doi.org/10.1007/s11846-018-0303-2>.
34. Kurniawan, -, Maulana, A., & Iskandar, Y. (2023). The effect of technology adaptation and government financial support on sustainable performance of MSMEs during the COVID-19 pandemic. *Cogent Business & Management*, 10(1), Article 2177400. <https://doi.org/10.1080/23311975.2023.2177400>.
35. Kyere, M., & Ausloos, M. (2021). Corporate governance and firms financial performance in the United Kingdom. *International Journal of Finance & Economics*, 26(2), 1871–1885. <https://doi.org/10.1002/ijfe.1883>.
36. Langevang, T., Steedman, R., Alacovska, A., Resario, R., Kilu, R. H., & Sanda, M.-A. (2022). The show must go on!: hustling through the compounded precarity of Covid-19 in the creative industries. *Geoforum*, 136, 142–152. <https://doi.org/10.1016/j.geoforum.2022.09.015>.

37. Lazzeretti, L., Oliva, S., Innocenti, N., & Capone, F. (2025). Rethinking culture and creativity in the digital transformation. *European Planning Studies*, 33(5), 671–679. <https://doi.org/10.1080/09654313.2022.2052018>.
38. Lee, L., & Liu, Y. S. (2024). The impact of major infectious disease events and government relief packages on the film industry: evidence from Taiwan. *Humanities & Social Sciences Communications*, 11, Article 1434. <https://doi.org/10.1057/s41599-024-03981-8>.
39. Lerro, A., Schiuma, G., & Manfredi, F. (2022). Entrepreneurial development and digital transformation in creative and cultural industries: trends, opportunities and challenges. *International Journal of Entrepreneurial Behavior & Research*, 28(8), 1929–1939. <https://doi.org/10.1108/IJEBr-11-2022-008>.
40. Lin, C. W., Tan, W. P., Lee, S. S., & Mao, T. Y. (2021). Is the improvement of CSR helpful in business performance? Discussion of the interference effects of financial indicators from a financial perspective. *Complexity*, 2021(1), Article 4610097. <https://doi.org/10.1155/2021/4610097>.
41. Liu, Y. S. (2021). Investor sentiment, trading activity and effect of the open-market share repurchase basing on firm characteristics. *Spanish Journal of Finance and Accounting*, 50(1), 39–64. <https://doi.org/10.1080/02102412.2019.1706882>.
42. Liu, Y. S., & Lee, L. (2022a). Policy and political effects on tourism development. *Tourism Analysis*, 27(4), 437–445. <https://doi.org/10.3727/108354222X16586121615173>.
43. Liu, Y. S., & Lee, L. (2022b). Are modifications in the ETF's investment performance and risks during the COVID-19 pandemic event?. *Review of Applied Socio-Economic Research*, 23(1), 5–17. <https://doi.org/10.54609/reaser.v23i1.202>.
44. Liu, Y. S. (2025a). The impact of organizational reform on the operational performance of Taiwan's commercial bank: assessment using the CAMELS rating system. *ECONOMICS-Innovative and Economic Research Journal*, 13 (2). <https://doi.org/10.2478/eoik-2025-0050>.
45. Liu, Y. S. (2025b). The impact of major infectious disease events on shareholder wealth and risks in cultural and creative industries. *Journal of Open Innovation: Technology, Market, and Complexity*, 11(3), Article 100582. <https://doi.org/10.1016/j.joitmc.2025.100582>.
46. Lu, Q., & Chesbrough, H. (2022). Measuring open innovation practices through topic modelling: revisiting their impact on firm financial performance. *Technovation*, 114, Article 102434. <https://doi.org/10.1016/j.technovation.2021.102434>.
47. Mahssouni, R., Makhroute, M., Touijer, M. N., & Elabjani, A. (2023). Dual perspectives on financial performance: analyzing the impact of digital transformation and COVID-19 on European listed companies. *Journal of Risk and Financial Management*, 16(8), Article 371. <https://doi.org/10.3390/jrfm16080371>.
48. Meuer, J., Koelbel, J., & Hoffmann, V. H. (2020). On the nature of corporate sustainability. *Organization & Environment*, 33(3), 319–341. <https://doi.org/10.1177/1086026619850180>.
49. Nasta, L. (2025). Understanding digital transformation in creative and cultural industries: a review. *Navigating the Paradoxes of Digital Transformation in the Creative and Cultural Industries: Embracing Innovation*, 7–22. https://doi.org/10.1007/978-3-031-77473-7_2.
50. Peñarroya-Farell, M., & Miralles, F. (2022). Business model adaptation to the COVID-19 crisis: strategic response of the Spanish cultural and creative firms. *Journal of Open Innovation: Technology, Market, and Complexity*, 8(1), Article 39. <https://doi.org/10.3390/joitmc8010039>.
51. Petrucci, F., & Milanesi, M. (2022). It ain't over till it's over: exploring the post-failure phase of new ventures in business networks. *Journal of Business & Industrial Marketing*, 37(13), 64–76. <https://doi.org/10.1108/JBIM-12-2020-0537>.
52. Protogerou, A., Kontolaimou, A., & Caloghirou, Y. (2022). Creative industries and resilience in times of crisis: the role of firm and entrepreneurial team characteristics. *International Journal of Entrepreneurial Behavior & Research*, 28(4), 1075–1105. <https://doi.org/10.1108/IJEBr-09-2021-0701>.

53. Rababah, A., Al-Haddad, L., Sial, M. S., Chunmei, Z., & Cherian, J. (2020). Analyzing the effects of COVID-19 pandemic on the financial performance of Chinese listed companies. *Journal of Public Affairs*, 20(4), Article e2440. <https://doi.org/10.1002/pa.2440>.
54. Ryu, S., Xiang, Y., & Zhang, W. (2024). Digital transformation of traditional cultural and creative industry. In *Guide to Digital Innovation in the Cultural and Creative Industry*. SAGE Publications, Inc. <https://doi.org/10.4135/9781071910023.n4>.
55. Santoro, G., Bresciani, S., & Papa, A. (2020). Collaborative modes with cultural and creative industries and innovation performance: the moderating role of heterogeneous sources of knowledge and absorptive capacity. *Technovation*, 92, Article 102040. <https://doi.org/10.1016/j.technovation.2018.06.003>.
56. Schalck, C., & Yankol-Schalck, M. (2021). Predicting French SME failures: new evidence from machine learning techniques. *Applied Economics*, 53(51), 5948–5963. <https://doi.org/10.1080/00036846.2021.1934389>.
57. Shin, S. (2025). The impact of COVID-19 on cultural and arts activities: evidence from a large-scale micro-level survey in South Korea. *Journal of Cultural Economics*, 49(1), 193–229. <https://doi.org/10.1007/s10824-024-09501-5>.
58. Shpak, N., Podolchak, N., Karkovska, V., Sroka, W., & Horbal, N. (2022). The application of tools for assessing the financial security of enterprises. *Forum Scientiae Oeconomia*, 10(2), 29–44. https://doi.org/10.23762/FSO_VOL10_NO2_2.
59. Skocdopole, P., Skypalova, R., & Fitala, P. (2023). Sustainable Strategic Management: Foreign Capital Participation in the Post-COVID-19 Era. *Forum Scientiae Oeconomia*, 11(3), 189–207. https://doi.org/10.23762/FSO_VOL11_NO3_10.
60. Smrt, M., Hodinova, A., & Kuchar, R. (2025). Impact of COVID-19 on stock prices in the global video game market. *Forum Scientiae Oeconomia*, 13(1), 8–20. https://doi.org/10.23762/FSO_VOL13_NO1_1.
61. Snowball, J. D., & Gouws, A. (2023). The impact of COVID-19 on the cultural and creative industries: determinants of vulnerability and estimated recovery times. *Cultural Trends*, 32(3), 207–230. <https://doi.org/10.1080/09548963.2022.2073198>.
62. Song, H. J., Yeon, J., & Lee, S. (2021). Impact of the COVID-19 pandemic: evidence from the US restaurant industry. *International Journal of Hospitality Management*, 92, Article 102702. <https://doi.org/10.1016/j.ijhm.2020.102702>.
63. Stefanovic, N., Barjaktarovic, L., & Bataev, A. (2021). Digitainability and financial performance: evidence from the Serbian banking sector. *Sustainability*, 13(23), Article 13461. <https://doi.org/10.3390/su132313461>.
64. Ullah, S. (2023). Impact of COVID-19 pandemic on financial markets: a global perspective. *Journal of the Knowledge Economy*, 14(2), 982–1003. <https://doi.org/10.1007/s13132-022-00970-7>.
65. Vitálišová, K., Borseková, K., Vaňová, A., & Helie, T. (2021). Impacts of the COVID-19 pandemic on the policy of cultural and creative industries of Slovakia. *Scientific Papers of the University of Pardubice. Series D. Faculty of Economics and Administration*, 29(1). <https://doi.org/10.46585/sp29011241editorial.upce.cz/SciPap>.
66. Wall-Andrews, C., Walker, E., & Cukier, W. (2021). Support mechanisms for Canada's cultural and creative sectors during COVID-19. *Journal of Risk and Financial Management*, 14(12), Article 595. <https://doi.org/10.3390/jrfm14120595>.
67. Wang, Y., Witman, A. E., Cho, D. D., & Watson, E. D. (2022). Financial outcomes associated with the COVID-19 pandemic in California hospitals. *JAMA health forum*, 3(9), e223056–e223056. <https://doi.org/10.1001/jamahealthforum.2022.3056>.
68. Williams, K., Lester, L., & Seivwright, A. (2024). The invisible architecture of creative and cultural work: the relationship between miscategorization and sector wellbeing during COVID-19. *Creative Industries Journal*, 17(3), 400–418. <https://doi.org/10.1080/17510694.2022.2106091>.

69. Yang, S. S., Huang, J. W., & Li, W. H. (2024). Institutional investor stewardship and material sustainability information: evidence from Taiwan. *Pacific-Basin Finance Journal*, 85, 102382. <https://doi.org/10.1016/j.pacfin.2024.102382>.
70. Yue, A. (2022). Conjunctions of resilience and the Covid-19 crisis of the creative cultural industries. *International Journal of Cultural Studies*, 25(3-4), 349–368. <https://doi.org/10.1177/13678779221091293>.
71. Zhang, D., & Fang, Y. (2022). Are environmentally friendly firms more vulnerable during the COVID-19 pandemic?. *Journal of Cleaner Production*, 355, Article 131781. <https://doi.org/10.1016/j.jclepro.2022.131781>.
72. Zhang, R., Ji, H., Pang, Y., & Suo, L. (2022). The impact of COVID-19 on cultural industries: an empirical research based on stock market returns. *Frontiers in public health*, 10, Article 806045. <https://doi.org/10.3389/fpubh.2022.806045>.
73. Zhao, X., Shen, L., & Jiang, Z. (2024). The impact of the digital economy on creative industries development: empirical evidence based on the China. *PLoS ONE* 19(3), Article e0299232. <https://doi.org/10.1371/journal.pone.0299232>.
74. Zhou, G., Liu, L., & Luo, S. (2022). Sustainable development, ESG performance and company market value: mediating effect of financial performance. *Business Strategy and the Environment*, 31(7), 3371–3387. <https://doi.org/10.1002/bse.3089>.

Identification of Key Indicators, Model Development, and Validation Methods for Bankruptcy Prediction: A Systematic Review for the Visegrad Group

Sebastian Klaudiusz Tomczak^{1,*}, Michal Karas², Tamas Kristo³, Lucia Duricova⁴, Marek Durica⁵

¹ Department of Operations Research and Business Intelligence, Wrocław University of Science and Technology, 27 Wybrzeże Stanisława Wyspiańskiego st. 50-370 Wrocław, Poland
ORCID: 0000-0003-3528-3533
e-mail: sebastian.tomczak@pwr.edu.pl

² Brno University of Technology, Kolejní 2906/4, Kralovo Pole, 61200, Brno, the Czech Republic
ORCID: 0000-0001-8824-1594
e-mail: michal.karas@vut.cz

³ Corvinus University of Budapest, Fovam ter 8, Budapest, 1093, Budapest, Hungary
ORCID: 0000-0003-2805-4900
e-mail: tamas.kristof@uni-corvinus.hu

⁴ Department of Economics, University of Zilina, Univerzitná 8215/1, Zilina, 010 26, Zilina, Slovakia
ORCID: 0000-0002-4722-4103
e-mail: lucia.duricova@uniza.sk

⁵ Department of Quantitative Methods and Economic Informatics, University of Zilina, Univerzitná 8215/1, Zilina, 010 26, Zilina, Slovakia
ORCID: 0000-0002-2118-166X
e-mail: marek.durica@uniza.sk

* Corresponding author: Sebastian Klaudiusz Tomczak, sebastian.tomczak@pwr.edu.pl

Abstract

Companies persist in encountering difficulties in navigating market conditions. To remain viable in the market, one must adapt rapidly to avoid obsolescence. These characteristics demonstrate increased diversity in the context of emerging markets, such as the Visegrad Group countries (V4). A multitude of financial distress models have been developed within the V4 to date. However, specialists from particular countries have yet to be convened for a comprehensive analysis of these models. The prior assessments overlook several publications. The objective of the article is to provide a novel comprehensive analysis of bankruptcy prediction models developed for the V4 countries and for the whole V4 region. It analyses the scientific publications associated with the development of bankruptcy prediction models from 1990 to 2024. Consequently, 180 works have been examined, encompassing more than 400 models. The review and analysis of bankruptcy prediction studies pertaining to the V4 were conducted by scrutinising the relevant scientific literature. In the study, we selected publications derived mostly from the Google Scholar and ResearchGate databases covering the period from Q1 1990 to Q1 2024. The Kruskal–Wallis test, a nonparametric ANOVA, was employed to analyse the ranks of the measurement values of the ratios. The test was derived from a sample including more than 200,000 companies throughout the period of 2006–2021 from the V4. The results indicate that statistical approaches remain the most prevalent; however, their accuracy is inferior to that of machine learning methods. The number of ratios incorporated in the V4 models fluctuates between three and eight indicators. Nonetheless, only a select few are frequently included in the models, including the total debt ratio (DR), equity ratio (ER), current liquidity ratio (CR), quick ratio (QR), return on assets (ROA) and return on equity (ROE). Thus far, no attempts have been made to utilise text analysis to assess the value of off-balance-sheet

Cite as:

Tomczak S. K., Karas, M., Kristof, T., Duricova, L., & Durica, M. (2025). Identification of Key Indicators, Model Development, and Validation Methods for Bankruptcy Prediction: A Systematic Review for the Visegrad Group. *Forum Scientiae Oeconomia*, 13(3), 156–196. https://doi.org/10.23762/FSO_V OL13_NO3_7

Received: 17 April 2025

Revised: 15 July 2025

Accepted: 28 August 2025



Copyright: © 2025 by the authors. For open-access publication within the terms and conditions of the Creative Commons Attribution (CC BY) licence (<https://creativecommons.org/licenses/by/4.0/>).

information for enterprises operating in the V4. It is noteworthy that, to date, no efforts have been undertaken in Hungary to publish the validation of any previously constructed models by independent academic researchers. The research was executed by specialists from each assessed V4 country, who had previously developed models for their respective countries. Studies published in both English and local languages (Czech, Hungarian, Polish, and Slovak) were considered. To the authors' knowledge, this is the inaugural comprehensive examination of models developed in the V4. We also checked the statistical significance of the values of the most used ratios in research and models among the V4 countries by using nonparametric ANOVA. Based on the results, we recommend verifying the accuracy of existing models using the most up-to-date large research database, and suggest checking the usefulness of text analysis for assessing the financial condition of companies.

Key words

model validation, financial and nonfinancial ratios, statistical methods, artificial intelligence methods, ANOVA.

Introduction

Enterprises in a market economy are perpetually evaluated by owners, suppliers, managers, business partners, and prospective investors. In developed countries, the Western market economy has functioned for a far longer duration than in post-communist economies, which transitioned to free market systems at a later stage. In this context, more approaches for evaluating enterprises have been constructed, particularly for advanced economies, where the operational history of businesses is significantly longer, resulting in better data accessibility.

Initially, financial ratio analysis was employed to evaluate the company's ratios to industry benchmarks throughout the 19th century. Subsequently, efforts were undertaken to identify ratios that exhibited certain capabilities, such as better predictive power (Fitzpatrick, 1932). As statistical methods evolved, novel approaches for evaluating organisations emerged, including univariate discriminant analysis (Beaver, 1966), multivariate discriminant analysis (Altman, 1968), and logit analysis (Ohlson, 1980). Alongside statistical approaches, further advancements included techniques rooted in artificial intelligence, such as neural networks (Messier Jr & Hansen, 1988), self-organising maps (Kohonen, 1997), and genetic algorithms (Varetto, 1998). In post-communist countries, including the Visegrad Group (V4), bankruptcy prediction models began to be developed only in the 1990s.

A multitude of reviews about models designed for developed markets has been utilised so far, which is, of course, a result of the aforementioned factors. The most significant include those by Kumar and Ravi (2007), Bellovary et al. (2007), and Ahmed et al. (2022). The first two date to 2007 and have each been cited over 1,000 times, while the newest, produced less than three years ago, has already received almost 250 citations. Bellovary et al. (2007) examined more than 170 studies on bankruptcy prediction from 1930 to 2007, detailing the prevalence of specific bankruptcy prediction methodologies, the quantity of indicators utilised in the research (enumerating the frequency of indicator occurrence in the models), whether the models underwent testing, and their accuracy in classification. Kumar and Ravi (2007) conducted a review of bankruptcy prediction in banks and enterprises from 1968 to 2005. The review included 128 publications, detailing the ratios, methodologies, samples, and dataset timelines for each study. Ahmed et al. (2022) examined 348 works related to artificial intelligence and machine learning in finance from 2011 to 2021, with a minority addressing bankruptcy prediction and credit risk assessment. They evaluated the most prolific and impactful countries, undertook citation analysis, identified the most pertinent academic sources, and recognised the most relevant authors. Identifying particular authors from the V4 in the offered works is challenging, as the initial models were developed in their respective native languages: Czech, Hungarian, Polish, and Slovak. Furthermore, several papers had not yet been indexed in

scientometric databases and lacked unique DOI identifiers. This article seeks to address the highlighted research gap by providing a comprehensive assessment of journal articles concerning corporate bankruptcy prediction in the V4.

The paper is structured as follows. Section 2 reviews the literature on bankruptcy prediction related to the V4. Section 3 outlines the methodology. Section 4 presents the results. Section 5 contains the discussion, while Section 6 delineates conclusions and recommendations for future research.

1. Literature review

There are a few summary studies on bankruptcy prediction models developed for particular V4 countries. The inaugural review, including authors from the V4 countries (Alaka et al., 2018) was published in 2017. This research presents a comprehensive review of 49 journal articles published from 2010 to 2015. The authors provide a comprehensive overview of the literature employing prevalent methodologies for bankruptcy prediction, including multiple discriminant analysis (MDA), logistic regression (LR), neural networks (NN), support vector machines (SVM), rough sets (RST), case-based reasoning (CBR), decision trees (DT), and genetic algorithms (GA). Through a systematic review, they identify 13 essential criteria: accuracy, result transparency, nondeterminism, sample size, data dispersion, variable selection method, multicollinearity, variable types, variable relationships, assumptions imposed by tools, sample specificity/overfitting, updateability, and integration capability. The subsequent two studies by Kral et al. (2018) and Prusak (2018), have already focused on the V4 countries. Kral et al. (2018) succinctly outline selected studies on the models developed in Czechia, Hungary, Poland, and Slovakia. Prusak (2018) examines a far greater number of models developed over a broader array of countries, specifically focusing on Central and Eastern European nations. A far more comprehensive study of the models was conducted by Kovacova et al. (2019) The review considers 103 bankruptcy prediction models developed in the V4 from 1993 to 2018. The authors determined the quantity of prediction models in various countries, the methodologies employed for model development, the number of explanatory variables incorporated in the models, the most often utilized ratios inside the models, and conducted a cluster analysis. The subsequent work (Kristóf & Virág, 2020) focuses on the examination of models specifically developed for the Hungarian economy. The authors do a comprehensive examination of the models, including the year of inception, ratios, sample size, research techniques, and classification accuracy. One of the two most recent papers (Prusak & Karas, 2024) compares the status of bankruptcy prediction research among the V4 nations and in connection to worldwide trends, while also conducting a bibliometric analysis. The final study (Dasilas & Rigani, 2024) focuses on bankruptcy prediction models covering the period from 2012 to mid2023. The researchers examined 207 publications, evaluating the most prevalent machine learning algorithms employed, data samples, accuracy, the most cited paper, and leading journals. They concentrate on the global context rather than only on the V4 countries.

Among the review studies on bankruptcy prediction models, only four pertain to all the V4 countries. Only two of them, Kral et al. (2018) and Prusak (2018), engaged with the authors of the works without doing a thorough analysis of the offered models. Conversely, two more studies Kovacova et al. (2019) and Prusak and Karas (2024) exclude several publications from the examined countries, neglecting some significant and highly referenced articles. This is attributable to the publication of some works in the local language of specific countries and the initial absence of particular DOI codes, rendering them inaccessible in various databases such as Scopus and Web of Science. Ultimately, no research was conducted by specialists from particular countries (four authors from different countries of the V4); there were simply fewer contributors, and most frequently, they were experts pertaining to their own countries. Consequently, specialists from each V4 country convened to compile this comprehensive analysis of bankruptcy prediction models for the period 1990 to 2024.

2. Methodology

The objective of the research is to identify the principal variables pertinent to bankruptcy prediction or financial distress studies across the V4, comprising Czechia, Hungary, Poland, and Slovakia. Consequently, the review and analysis of bankruptcy prediction studies pertaining to the V4 were conducted by examining the relevant scientific literature. In the study, we selected publications derived mostly from the Google Scholar and ResearchGate databases covering the period from Q1 1990 to Q1 2024. The research was executed by specialists from each assessed V4 country, who had previously developed models for their respective countries. Studies published in both English and local languages (Czech, Hungarian, Polish, and Slovak) were considered. To the authors' knowledge, this is the inaugural such huge comprehensive examination of models developed in the V4.

The article examines the models, their accuracy, the methodology used, the research period, the sample size, as well as the indicators present in these models and those considered in the studies. This comprehensive study of indicators facilitates the identification of the most prevalent indicators utilised in empirical research and final models. First, the models were individually examined for each V4 country. Second, the efficacy of the models was assessed based on a literature review. Third, the indicators present in both the studies and the models were examined. Finally, a comprehensive analysis was conducted. In that section, we analyse the most frequently used ratios in research and models based on the sample retrieved from the EMIS database (EMIS stands for Emerging Markets Information Service, a Euromoney Institutional Investor Company, www.emis.com). The sample consists of more than 200,000 companies in the period of 2006–2021, with more than 1,000,000 company-year observations used in the sample and covers four countries: Czechia, Hungary, Poland, and Slovakia. We use non-parametric analysis of variance (ANOVA), the so-called Kruskal-Wallis test. The ANOVA is a frequently used method for analysing dissimilarities between the averages/medians of two or more groups. In this particular case, differences between the values of each ratio in four countries are checked.

The Kruskal–Wallis test, as a nonparametric ANOVA, does not require a normal distribution of the values of the ratios. Similar to other nonparametric tests, it is carried out on the ranks of the measurement values of the ratios. A rank of 1 is assigned to the smallest value, a rank of 2 is assigned to the second smallest, etc. The sum of the ranks, R_i , is computed for each group, i ($i = 1, 2, \dots, C$), of size n_i , and then the test statistic, H , is computed (Kruskal & Wallis, 1952). The H is approximately Chi-squared-distributed, with the degrees of freedom equal to the number of groups, C , minus 1.

$$H = \frac{12}{N \cdot (N+1)} \sum_{i=1}^C \frac{R_i^2}{n_i} - 3(N+1) \quad (1)$$

where C is the number of groups; n_i is the number of observations in the i th group; $N = \sum n_i$ is the number of observations in all groups combined; and R_i is the sum of the i -th group.

The following hypotheses were tested:

Hypothesis 0 (H_0). The different samples in the comparison were drawn from the same distribution, or from distributions with the same median.

Hypothesis 1 (H_1). The different samples in the comparison were not drawn from the same distribution, or from distributions with the same median.

The analysis of the Kruskal–Wallis test is very similar to the abovementioned ANOVA. The test is based on ranks instead of means. If the null hypothesis was rejected, various comparisons of the average ranks for all groups were carried out. The comparisons are computed as the post hoc analysis of the average ranks of all pairs of groups (Siegel & Castellan, 1988). The z values for each comparison between groups u and v can be calculated as:

$$Z_{u,v} = \frac{|\bar{R}_u - \bar{R}_v|}{\sqrt{\frac{N(N+1)}{12} \left(\frac{1}{n_u} + \frac{1}{n_v} \right)}} \quad (2)$$

where $\bar{R}$ indicates the mean ranks for the two groups, and n_u and n_v represent the number of observations in the two groups (u and v, respectively).

Each company is assigned to only one group (country), which means that samples are independent. The number of companies included in each country differed, and consisted of 8,315 companies for Czechia, 8,857 companies for Slovakia, 31,241 companies for Hungary, and 73,747 companies for Poland. The number of companies in different years also differs.

The subsequent research questions have been established to facilitate the study:

RQ1: What methods are applied to predict the bankruptcy of firms within the V4?

RQ2: Has the model's accuracy been validated?

RQ3: Do the researchers' analyses of individual model accuracy align with the accuracy reported by the model authors?

RQ4: What are the most commonly used indicators in models and studies in the V4?

RQ5: Are the differences between the values of the selected ratios between countries statistically significant?

RQ6: What is the number of indicators utilised in the study and models across the V4?

RQ7: What sample sizes were utilised to develop the models?

RQ8: In which journals do the authors of the models disseminate their research?

3. Research results

3.1 Analysis of Bankruptcy Prediction Models in the V4 Group

The analysis encompassed four countries, namely Czechia, Hungary, Poland, and Slovakia, together with the V4 group as a whole. Table 1 features 21 papers pertaining to Czechia, Table 2 enumerates 31 articles for Hungary, Table 3 displays 49 articles for Poland, Table 4 encompasses 39 articles for Slovakia, and Table 5 presents 7 articles for the V4 as a whole from the first quarter of 1990 to the first quarter of 2024. A total of 147 articles were included in the analysis, 33% for Poland 27% for Slovakia, 21% for Hungary, 14% for Czech, and 5% for the V4.

3.2 Analysis of Models in Czechia

Table 1 contains 21 publications in which a total of 73 models were developed and published. The history of bankruptcy prediction models began with the IN family of models expanding from 1995 to 2005, providing the names to the models – IN95, IN99, IN01, and IN05. The IN05 model was the first model presented at a scientific conference in 2005 (Neumaier & Neumaierová, 2005).

Table 1. Bankruptcy prediction models constructed for the Czech economy.

Model	No. of methods	Best method	Accuracy	Sample size	Period	Sector	No. of ratios	Selection criteria	No. of ratios in model
Neumaier and Neumaierová (2005)	1 (2)	MDA	97 % (B) / 92 % (A)	1,526	2005	M	nd	nd	5
Dvořáček et al. (2008)	1(1)	MDA	70% (B)/ 100% (A)	73	nd	MINI	8	BTH	8
Jakubík and Teplý (2011)	1(1)	LR	80.41 % (Gini)	31,612	1993-2005	nd	22	STW	7
Dvořáček et al. (2012a)	3(3)	ANN	90 % (A) / 100 % (B)	186	1996-2010	nd	8	FS	8
Dvořáček et al. (2012b)	1(4)	MDA	85 % (A) / 92% (B)	170	1997-2008	M, C, AG, SE	10	nd	5-8 (7)
Valecký and Slivková (2012)	1(1)	LR	0,8625 (AUC)	400	2008	nd	19	STW	4
Kalouda and Vaníček (2013)	1(2)	MDA	0,853 (AUC)	538,162	nd	nd	39	DP	8
Karas and Režňáková (2013)	1(1)	MDA	78 % (A) / 92 % (B)	207	2007-2010	M	38	STW	3
Karas and Režňáková (2014)	2(5)	Boosted trees	92 % (A) / 96 % (B)	1,908	2004-2011	M	38	RI	5

Bemš et al. (2015)	5(18)	magic square	30 % (Gini)	3,120	nd	nd	5	GINI	5
Machek et al. (2015)	2(2)	MDA	78%	3,158	nd	CB	5	ALV	5
Vochozka et al. (2015a)	1(1)	LR	92%	12,930	2003-2012	TR	nd	SIG	12
Vochozka et al. (2015b)	1(6)	ANN	94%	15,189	2003-2013	C	100	nd	nd
Němec and Pavlík (2016)	1(1)	LR	84%	241,38	2005-2013	G	30	UA	6
Slaviček and Kuběnka (2016)	1(4)	LR	0,94 (AUC)	33	2013	C	12	MA, AAR	4
Vochozka et al. (2016)	1(1)	ANN	0,963 (AUC)	67,000	2003-2013	M	91	FS	91
Karas and Režňáková (2017)	1(2)	CART	62% (A) / 92 % (B)	1,540	2011-2014	C	29	CART	5
Vochozka (2017)	1(10)	MLP	94.40%	65,536	2008-2014	C	90	NN	6
Karas and Režňáková (2018)	1(6)	MDA	0,889 (AUC)	1,355	2011-2014	C	28	STW	5
Karas and Srbová (2019)	1(1)	MDA	77,28 % (A) / 86 % (B)	4,420	2011-2015	C	35	STW	4
Karas and Režňáková (2020)	3 (3)	CART + PCA + LR	0,82 (AUC)	4,350	2013-2018	M	31	PCA + CART	6

Note: AAR – all areas of group of ratios, AG – agribusiness, ALV – variables from Altman's model, BTH – Based theory, C – construction, CB – Cultural business, CART - Classification And Regression Trees, DP- discrimination power, FS – full set, G – general, GINI- Gini coefficient, M – manufacturing, MA – maximum of accuracy, MINI – mining, nd – no data, PCA – principal component analysis, RI – relative importance, SE – service, SIG – significance test, STW stepwise, TR- Transport, UA – univariate analysis.

Source: Neumaier and Neumaierová (2005), Dvořáček et al. (2008), Jakubík and Teplý (2011), Dvořáček et al. (2012a), Dvořáček et al. (2012b) Valecký and Slivková (2012), Kalouda and Vaníček (2013), Karas and Režňáková (2013), Karas and Režňáková (2014), Bemš et al. (2015), Machek et al. (2015), Vochozka et al. (2015a), Vochozka et al. (2015b), Němec and Pavlík (2016), Slaviček and Kuběnka (2016), Vochozka et al. (2016), Karas and Režňáková (2017), Vochozka (2017), Karas and Režňáková (2018), Karas and Srbová (2019), Karas and Režňáková (2020).

From 2005 to 2019, there were 21 separate articles published proposing new or updated bankruptcy models, particularly created for Czech companies. Most of the models (81%) were published between 2012 and 2018. The models vary in several dimensions, including the classification algorithm utilised, the variable selection methodology, and the approach to accuracy assessment. Methodologically, the predominant technique for model development was MDA at 41%, followed by the LR (23%) and NN (14%). Approximately one third of these models (31%) are designed as generic models, indicating that they do not concentrate on a specific industry sector. The industry-specific models predominantly focused on construction enterprises (27.3% of cases) and manufacturing enterprises (22.7% of cases). Due to the varied accuracy metrics employed by different authors, it is challenging to ascertain which method achieved the maximum accuracy in the context of Czech models. Five of the nine studies utilising the MDA technique employ genuine positive rate metrics, with the rate for bankrupt firms ranging from 70% to 97%, and for nonbankrupt enterprises from 78% to 100%. It is important to note that not all research references these figures as out-of-sample data. Two studies report Area Under Curve (AUC) values of 0.853 and 0.889, while the other two provide overall accuracy of 78% and 84.8%. The authors employed the logit technique, utilising AUC measurements of 0.8625 and 0.94, alongside overall accuracy and a Gini coefficient (GINI) of 80.4%, which corresponds to an AUC of 0.9205.

The models have the characteristic of often analysing a relatively short time frame, occasionally limited to a single period (Neumaier & Neumaierová, 2005; Valecký & Slivková, 2012; Slaviček & Kuběnka, 2016), while for four models, the particular time period was not disclosed. The most extended analysed period was 14 years for model (Dvořáček et al., 2012a) and 12 years for model (Jakubík & Teplý, 2011). The average duration of the analysed period is 6.1 years. Another characteristic that distinguishes the models is the methodology employed to obtain the set of model variables. In one third of the analysed models, there was no reduction in the set of ratios established. In other instances, the array of possible ratios was not elaborated upon and was only referenced, for example, as 100 corporate characteristics. The analysis of financial ratios varies from 10 in the case of

the Dvořáček et al. (2012b) model to 39 in the Kalouda and Vaníček (2013) model, contingent upon the supplied list of potential variables. Some authors, for example Vochozka and Rowland (2015) and Vochozka et al. (2016) utilised artificial neural networks to manage a substantial number of variables and incorporated 91 or about 100 firm features.

3.2 Analysis of Models in Hungary

A total of 121 models has been developed and published within the context of the 31 Hungarian references. Only conventional statistical techniques (MDA, LR) were used in 16 scholarly articles, representing 51.6% of the sources (Table 2).

Table 2. Bankruptcy prediction models constructed for the Hungarian economy.

Model	No. of methods	Best method	Accuracy	Sample size	Period	Sector	No. of ratios	Selection criteria	No. of ratios in model
Hajdu and Virág (2001)	2 (2)	LR	82%	154	1990-1991	G	16	STW	5
Virág and Kristóf (2005)	3 (8)	NN	86%	154	1990-1991	G	16	BAC	16
Virág and Kristóf (2006)	4 (4)	NN	87%	154	1990-1991	G	16	BAC	16
Kristóf	4 (4)	NN	84%	504	2004-2005	G	31	PCA, EPR	5
Virág and Kristóf (2009)	1 (1)	LR	94%	100	2004	G	31	PROXSICAL, STW	31
Bozsik (2011)	3 (5)	BF-ANN-DT	84%	400	2009	G	16	DT, RRP	16
Kristóf and Virág (2012)	4 (12)	NN	94%	504	2004-2005	G	31	PCA, CHAID, PRI	15
Virág and Nyitrai (2013)	2 (2)	SVM	89%	156	1990-1991	G	17	t-test	10
Bareith et al. (2014)	1 (1)	NN	85%	8,004	2002-2012	G	10	PRI	8
Ékes and Koloszar (2014)	4 (4)	NN	73%	148	2011	G	31	BAC	31
Nyitrai (2014a)	1 (1)	CHAID	78%	1,000	2009-2012	G	17	CHS, DT	7
Nyitrai (2014b)	1 (1)	C4.5	76%	1,000	2004-2012	G	17	IG, DT	11
Virág and Nyitrai (2014a)	3 (3)	RST	89%	156	1990-1991	G	17	t-test, REP	5
Virág and Nyitrai (2014b)	1 (7)	C4.5	83%	976	2001-2012	G	17	BA, DT	17
Felföldi-Szűcs (2015)	1 (1)	LR	70%	905	2008	G	41	STW	12
Nyitrai (2015)	1 (1)	KNN	80%	1,000	2001-2012	G	17	t-test	7
Inzelt et al. (2016)	1 (1)	LR	86%	368,328	1999-2013	G	29	BA, DT, STT	5
Nyitrai (2017)	1(1)	LR	90%	2,094	2009-2015	G	20	BO, STW	11
Nyitrai and Virág (2017b)	1(4)	LR	81%	1,354	2001-2014	G	18	STW	12
Nyitrai and Virág (2017a)	1(2)	LR	91%	1,542	2001-2014	G	18	STW	11
Kristóf (2018)	4(4)	NN	82	1,828	2015-2016	G	28	PCA, LMA	28
Nyitrai (2018)	1(16)	LR	91%	2,614	2007-2015	G	25	STW	16
Sütő (2018)	2(2)	LR	83%	86	2009-2012	RTC	22	STW	8
Nyitrai (2019a)	1(5)	MDA	89%	2,098	2007-2016	G	20	CHAID, STW	8
Nyitrai (2019b)	4(4)	MDA	83%	3,370	2001-2015	G	17	CHAID, STW	6
Nyitrai and Virág (2019)	5(15)	MDA	87%	2,996	2007-2016	G	20	CHAID, STW	12
Szenes and Dabi (2020)	1(1)	LR	80%	286,445	2006–2017	G	27	WOE, GINI, COR	7
Horváth (2021)	1(1)	LR	78%	63,772	2007-2017	G	22	LASSO	15
Ágoston (2022)	6(6)	RF	84%	208	2014-2018	G	8	PRI, DT	8
Márton et al. (2023)	1(1)	LR	78%	190,982	2017-2018	G	26	CHAID, STW	9
Szántó (2023)	1(1)	LR	86%	1,677	2013-2021	C	19	STW	7

Note: BA – bagging, BAC – backpropagation, BO – bootstrap, CHS chi-squared, COR - correlation analysis, DT- decision trees, EPR - exhaustive prune, IG – information gain, LMA - Levenberg-Marquard algorithm, PRI - predictor importance, REP - recursive partitioning, RRP reduced error pruning, RTC - retail trade companies, STT – stability test, WOE - weight of evidence

Source: Hajdu and Virág (2001), Virág and Kristóf (2005), Virág and Kristóf (2006), Kristóf (2008), Virág and Kristóf (2009), Bozsik (2011), Kristóf and Virág (2012), Virág and Nyitrai (2013), Bareith et al. (2014), Ékes and Koloszar (2014), Nyitrai (2014a), Nyitrai (2014b), Virág and Nyitrai (2014a), Virág and Nyitrai (2014b), Felföldi-Szűcs (2015), Nyitrai (2015), Inzelt et al. (2016), Nyitrai (2017), Nyitrai and Virág (2017b), Nyitrai and Virág (2017a), Kristóf (2018), Nyitrai (2018), Sütő (2018), Nyitrai (2019a), Nyitrai (2019b), Nyitrai and Virág (2019), Szenes and Dabi (2020), Horváth (2021), Ágoston (2022), Márton et al. (2023), Szántó (2023).

The remaining articles (48.4%) employed at least one machine learning (ML) technique. The inaugural ML-based model was published in Hungary in 2005. In Hungary, the Bankruptcy Act introduced the foundations to statistically analyse bankruptcy prediction in the early 1990s. Over the years, significant progress has been made in Hungarian literature and the practice of bankruptcy prediction. The first Hungarian bankruptcy models were developed using financial data from 1990 and 1991, applying MDA and LR. Out of 154 industrial enterprises, 77 were financially stable and 77 experienced insolvencies in 1992. The models were first published in Hungarian and later in English in 2001 (Hajdu & Virág, 2001). Researchers subsequently experimented with various architectures to

construct NN-based models on the same database, resulting in a four-layer backpropagation network that demonstrated superior performance compared to the previous LR model (Virág & Kristóf, 2005). A more complex empirical study on the same database by employing the industrial mean relative ratios again found that NN outperformed traditional methods in terms of performance (Virág & Kristóf, 2006).

In 2008, a more recent database with a broader set of variables was compiled, and four techniques were applied. The NN model had the highest performance, with an Area Under the Receiver Operating Characteristic Curve (AUROC) of 0.84 (Kristóf, 2008). A LR model was developed one year later based on reduced-dimensional coordinates, resulting in exceptional classification accuracy, after transforming differences between solvent and insolvent observations into coordinates using Mahalanobis distance (MD) (Virág & Kristóf, 2009).

Bozsik (2011) demonstrated the effectiveness of integrating DT with NN by applying single-layer perceptron networks to C4.5 decision trees. The optimised brute force models achieved an accuracy rate of 84 percent in classification. A similar comparative empirical research article used a sample of 504 Hungarian enterprises to analyse the positive effect of chi-squared automatic interaction detection (CHAID) on model performance. Results demonstrated that the discretised variables substantially improved LR and NN models' performance (Kristóf & Virág, 2012).

An empirical examination by Virág and Nyitrai (2013) used SVM on a Hungarian corporate database, demonstrating superior classification performance compared to the benchmark NN model. Authors later applied the RST method to further experiment with ML techniques on Hungarian enterprises (Virág & Nyitrai, 2014a). They aimed to determine if sacrificing model interpretability for greater accuracy was justified. The results showed that RST, using clear 'if-then' rules, yielded comparable results to SVM, ensuring the balance between comprehensibility and effectiveness. The K-nearest neighbours (KNN) was used for Hungarian bankruptcy prediction in a study using a balanced sample of 1,000 observations (Nyitrai, 2015). The models were created using various k values, distance definitions, and variables from 1, 2, and 3 years prior to bankruptcy. The multi-period variables yielded the most favourable result, outperforming the one-year-previous model. A comparable study with CHAID also found similar conclusions (Nyitrai, 2014a). In a subsequent study using CBR as a comparative approach to KNN, 1,828 Hungarian micro-enterprises were analysed (Kristóf, 2018). Principal component analysis (PCA) was used to ensure independent input variables, and the nearest neighbours were identified using the reduced dimensionality tree (RDT) technique. The CBR model had higher classification accuracy than the DT and LR models, but lower accuracy than the benchmark NN model. An empirical research by (Virág & Nyitrai, 2014b) examined the effectiveness of ensemble approaches in analysing financial ratios of Hungarian enterprises from 2001 to 2012. The bagging technique was found to be the best solution. Results demonstrated that dynamic variables positively impacted model performance, but industrial mean ratios did not improve it. Other results also indicated that dynamization improves predictive power. By using indicator variables, models with minimum and maximum values from previous periods showed enhanced classification accuracy (Nyitrai, 2019b). By employing ten-fold cross-validation, all models demonstrated that incorporating dynamised variables led to enhanced classification accuracy in comparison to models built just using the original static variables. Generating category factors based on node number in CHAID also improved prediction capability compared to using original data as input variables (Nyitrai, 2019a). A study analysing the financial ratios of 1,542 Hungarian enterprises from 2001 to 2014 found that AUROC showed stronger model performance when considering more historical years. For companies less than 10 years old, including all available years of data was beneficial, while using the most recent 10 years of data yielded the greatest model performance (Nyitrai & Virág, 2017b). Another study also corroborated the findings on a different sample containing 1,354 companies (Nyitrai & Virág, 2017a). Researchers in Bareith et al. (2014) used a single hidden layer NN to predict insolvency of enterprises. Due to the repercussions of the financial crisis, the database was divided into two economic periods, 2002-2008 and 2009-2012, analysing financial

ratios from three historical years. The model performed better from 2002 to 2008, indicating its effectiveness in predicting insolvency. Nyitrai (2018) conducted a study to analyse the effects of firm size and industry on bankruptcy models. They used a sample of data from 2007-2015, consisting of 2,614 Hungarian enterprises. The LR models demonstrated that both business size and industry had a significant impact on the design and performance of bankruptcy models. Nyitrai (2017) conducted comprehensive research on the effect of linking stock balance sheet items to flow profit-and-loss statement items on the accuracy of bankruptcy prediction models. Nyitrai and Virág (2019) evaluated the impact of handling outliers on model performance using different approaches. The study determined that the use of CHAID for categorisation was more successful in managing outliers compared to the methods of coercing based on external percentiles or the mean of multiple standard deviations. A similar study conducted by Szántó (2023) investigated the effects of various outlier handling methods on model performance using a database of Hungarian construction companies. The most favourable approach in this research was the nearest neighbour's imputation.

A LR model was developed for companies in the retail sales sector residing in non-specialised stores in the Northern Great Plain region (Sütő, 2018). A study on Hungarian small and medium enterprises (SME) demonstrated that bankruptcy models for large corporations cannot be applied to SMEs with different financial behaviours (Ékes & Koloszár, 2014). Alternatively, the best model was found using NN. Research on firm insolvency using ML methods in Hungary's Pecs and Budapest regions found the RF model had the highest predictive power to assess bankruptcy risks (Ágoston, 2022). A comparative study on corporate credit risk models in Hungary found that incorporating behavioural and non-financial characteristics improved discriminatory power, outperforming models based solely on financial ratios (Felföldi-Szűcs, 2015).

Four published Hungarian corporate financial distress models were based on a relatively large database. Three of these models were developed by researchers from the National Bank of Hungary. The study of Inzelt et al. (2016) aimed to develop a supervisory corporate default model to facilitate the effective monitoring of Hungarian companies in the banking sector. The modelling database from the period 1999-2013 consisted of 368,328 companies. Horváth (2021) conducted empirical research using data from 63,772 companies to support credit risk stress testing and evaluate the susceptibility of corporate lenders based on individual client defaults that occurred from 2007 to 2017. For the purpose of establishing a standard model for evaluating internal corporate rating systems employed by Hungarian banks, Szenes and Dabi (2020) introduced a comprehensive and widely applicable benchmark model. This model was developed using historical data from 286,445 companies. A team of researchers Márton et al. (2023) created a bankruptcy model that evaluated the level of risk associated with Hungarian companies during the COVID-19 era. They utilised a dataset containing 190,982 records of corporate financial data.

Out of the total number of articles, 22 (71.0%) were published in various Hungarian journals, primarily in prestigious publication outlets within Hungary. Only 9 papers (29.0% of the total) on Hungarian bankruptcy models have been published in English scientific journals.

3.3 Analysis of models in Poland

A comprehensive examination of Table 3 reveals that a total of 352 models were constructed for the Polish economy, relying exclusively on 49 articles. By incorporating the models presented in monographs and at conferences, the number of models would be significantly increased.

In Poland during the early 1990s and 2000s, the construction of statistical models (SM) was limited to two main approaches: MDA and LR models. In recent years, there has been a proliferation of advanced models, such as the fuzzy logic model (FL), into the academic literature. In light of the growing prevalence of ML and artificial intelligence (AI) models, it is noteworthy that 65% of articles employed MDA, while 45% utilised LR. Furthermore, the decline in the utilisation of MDA and LR signifies a reduction in their proportion in the overall number of models generated. On average, statistical models account for 42% of the constructed models, with 82 models for MDA and 78 models for LR. In contrast, ML and AI techniques are present in 43% of the documented articles, with a total

of over 210 models developed, representing 57% of the overall models. Multimethod analysis articles encompass a range of statistical, ML, and AI techniques, wherein SM are juxtaposed with models derived from more advanced methodologies. Furthermore, a majority of the articles (53%) incorporated models that encompassed multiple sectors, while a smaller proportion (22%) focused solely on the manufacturing sector. Correlation analysis (COR) was the most commonly employed criterion for indicator selection, as evidenced by its usage in 13 articles. The stepwise (STW) method was utilised in 10 articles, while Wilks' lambda (W-L) statistic was employed in 7 articles. Furthermore, these criteria are primarily employed in the context of SM. The assumptions that ML and AI models must satisfy are comparatively fewer than those of SM. The levels of accuracy exhibited by the models presented in the articles differ across individual works. Both the minimum and maximum values are observed for MDA, with numerical values of 69% and 100%, respectively. It is important to note that the efficacy of SM can be readily validated, such as through the examination of existing literature. These findings will be presented in the subsequent section of the article.

Table 3. Bankruptcy prediction models constructed for the Polish economy.

Model	No. of methods	Best method	Accuracy	Sample size	Period	Sector	No. of ratios	Selection criteria	No. of ratios in model
Mączyńska (1994)	1 (1)	DA	-	nd	-	nd	6	ED	6
Pogodzińska and Sojak (1995)	1 (1)	DA	80%	10	1993	G	2	ED	2
Tarczyński (1996)	1 (1)	DA	69%	42	1995	G	14	nd	14
Tarczyński (1998)	1 (1)	DA	69%	42	1995	G	14	nd	14
Zawadzki and Babis (1998)	1 (1)	DA	100%	17	nd	RRSRF	40	COR, ED, STW	6
Wierzba (2000)	1 (1)	DA	92%	48	1995-1998	G	12	COR, STW	4
Appenzeller (2001)	1 (3)	DA	94%	56	1991-1997	G	16	S-W; SKC; K-S; W-L	4-7
Hołda (2001)	1 (1)	DA	93%	80	1993-1996	G	13	ED	5
Sojak and Stawicki (2001)	1 (3)	DA	93%	58	1998	G	20	k-means, WM, FAA	3-7
Appenzeller and Szarzec (2004)	1 (2)	DA	88%	68	2000-2002	G	19	COE R, STW	5-6
Gruszczyński (2004)	1 (4)	LR	91%	200	1995-1997	G	17	COR	2-3
Hamrol et al. (2004)	1 (1)	DA	96%	100	1999-2002	G	31	COE R, COR, W-L	4
Sojak and Konieczka (2004)	1 (4)	DA	97%	54	1996-2000	SR	24	WM	8-9
Wędzki (2005a)	1 (6)	LR	88%	2,300	2000-2003	G, C	21	S-W, UMW, STW	2-7
Wędzki (2005b)	1 (8)	LR	79%	80	2000-2003	G	20	COR	2-7
Wędzki (2005c)	1 (8)	LR	78%	80	2000-2003	G	20	CSV, KC, STW, COR	2-7
Mączyńska and Zawadzki (2006)	1 (7)	DA	97%	80	1997-2002	G	42	DIFM, DIFI, TIV, MD, COR, W-L	4-11
Korol (2010a)	4(24)	DA	96%	132	2000-2005	M, SE	28	nd	14
Korol (2010b)	7(52)	SSN REC	94%	185	2000-2005	M, SE	28	COR	28
Dębkowska (2012)	3(3)	CT	97%	68	2009	G	17	HM, COR	7
Pisula (2012a)	1(2)	LR	91	205	2004-2012	L	24	IV, GINI, Vcramer	6-20
Pisula (2012b)	3(15)	NN	92%	207	2007-2010	L	26	COR	3-26
Ptak-Chmielewska (2012)	3(3)	LR	85%	1,536	2002-2011	G	21	COR	9
Wędzki (2012)	1(11)	LR	83%	76	2001-2003	G	nd	STW	8
Dębkowska (2013)	2(12)	CT	97%	120	2010	G	14	HM, COR	10
Gąska (2013)	2(3)	SVM	90%	18	2008-2012	G	17	AUC	4
Korol (2013)	3(6)	CT	96%	185	2000-2007	M, SE	14	nd	3
Pisula et al. (2013)	3(8)	MLP	94%	66	nd	L	28	WM	6
Waszkowski (2013)	1(1)	L	78%	36	2010	G	20	COR	5
Balina and Juszczuk (2014)	3(3)	DA	93%	60	2007-2010	ICRTS	42	COR, STW, t-test	2-4
Juszczuk and Balina (2014)	1(4)	DA	91%	180	2007-2010	C, W, RTG, G	42	COR, t-test, NOR, MEV	3-4
Gąska (2015)	5(42)	SVM	76%	94	2008-2014	G	17	STD, BO, WMW	3-5
Pisula et al. (2015)	2(8)	MLP	95%	66	nd	L	28	IV, GINI, Vcramer	26
Rusiecki and Białek-Jaworska (2015)	2(3)	DA	98%	142	2009-2014	C	38	COR, J-B, SW	4-7
Wojnar (2015)	2(8)	DA, LR	92%	140	2012-2013	C, M	38	t-test, W-L	2-6
Zięba et al. (2016)	16(16)	EXGB	96%	10,700	2000-2012	M	64	DIS 0	64
Pisula (2017)	6(6)	NNet	98%	144	2008-2014	M	11	SUM, VCramer, IV	11

Pawełek and Grochowina (2017)	1(28)	Bagging	79%	7,223	2013-2015	M	16	RF	4
Wójcicka (2017)	2(6)	NN	97%	nd	2009-2015	C, M, T	25	DA	7-10
Balina (2018)	3(3)	DA	87%	60	2009-2013	W F M	42	COR, t-test	3-4
Durica et al. (2019a)	1(2)	CT	98%	29,000	2016-2017	G	37	ROC	3
Jaki and Ćwiąg (2020)	1(2)	DA	99%	44	2010-2015	C	20	COR, K-S, S-W, W-L	7-12
Pawełek et al. (2020)	4(32)	NN	81%	246	2005-2010	M	39	STW	3
Pisula (2020)	1(1)	GBM	99%	3,679	2018	G	22	GA	2-19
Tomczak (2020)	2(2)	DA	92%	10,700	2000-2012	M	64	K-S test, t-test, COR, W-L, STW	5
Geise et al. (2021)	1(1)	LR	89%	3,641	2017	C	17	z-test	7-17
Noga and Adamowicz (2021)	1(1)	DA	89%	135	2006-2012	WO	15	COR, W-L	5
Ptak-Chmielewska (2021)	2(2)	SVM	72%	806	2008-2010	G	21	t-test, CHS, COR	9
Kokczyński (2023)	1(10)	DA	75%	56	2017-2019	G	32	COR, STW, ED	5

Note: COE coefficient, CSV - cumulative share of variance, DIFI - distributions of indicators, DIFM difference of means, DIS - distribution, ED- expert decision, FAA - factor analysis, GA - genetic algorithms, HM - Hellwig's method, ICRTS - international commercial road transport sector, IV - Information Value, J-B - J-B Jarque-Bera, KC - Kaiser's criterion, K-S - Kolmogorov-Smirnov test, MD - Mahalanobis distance, MEV - multicollinearity of explanatory variables, NOR - normality test, RF - random forest, RRSRF - railway rolling stock repair facilities, SKC - Skewness and Kurtosis Coefficients, STD - Standardization, SUM - Symmetrical Uncertainty measure, S-W Shapiro-Wilk test, T - trade sector, TIV - trend in indicator values, UMW - Manna-Whitney, W-L - Wilks' Lambda test, WM- Ward method.

Source: Mączyńska (1994), Pogodzińska and Sojak (1995), Tarczyński (1996), Tarczyński (1998), Zawadzki and Babis (1998), Wierzbą (2000), Appenzeller (2001), Hołda (2001), Sojak and Stawicki (2001), Appenzeller and Szarzec (2004), Gruszczynski (2004), Hamrol et al. (2004), Sojak and Konieczka (2004), Wędzki (2005a), Wędzki (2005b), Wędzki (2005c), Mączyńska and Zawadzki (2006), Korol (2010a), Korol (2010b), Dębkowska (2012), Pisula (2012a), Pisula (2012b), Ptak-Chmielewska (2012), Wędzki (2012), Dębkowska (2013), Gąska (2013), Korol (2013), Pisula et al. (2013), Waszkowski (2013), Balina and Juszczak (2014), Juszczak and Balina (2014), Gąska (2015), Pisula et al. (2015), Rusiecki and Białek-Jaworska (2015), Wojnar (2015), Zięba et al. (2016), Pisula (2017), Pawełek and Grochowina (2017), Wójcicka (2017), Balina (2018), Durica, et al. (2019a), Jaki and Ćwiąg (2020), Pawełek et al. (2020), Pisula (2020), Tomczak (2020), Geise et al. (2021), Noga and Adamowicz (2021), Ptak-Chmielewska (2021), Kokczyński (2023).

Over 20 distinct methodologies were employed in the construction of bankruptcy prediction models across the 49 articles under analysis. The study of Zięba et al. (2016) employed the highest number of methods, totalling 16. The researchers considered the following methodologies: MDA; multilayer perceptron with a hidden layer (MLP); decision rules inducer (JRip); cost-sensitive variation of JRip (CJRip); decision tree model (J48); cost-sensitive variation of J48 (CJ48); LR; cost-sensitive variation of LR (CLR); adaBoost (AB); AdaCost (AC); SVM; cost-sensitive SVM (CSVM); random forest (RF); boosted trees trained with extreme gradient boosting (XGB); only the last tree of the ensemble of boosted trees, i.e., f K, trained with the Algorithm 1 (XGBE); ensemble of boosted trees trained with the Algorithm 1 (EXGB). The best performing models were derived from EXGB, achieving an accuracy rate of 96%. The level of accuracy was attained through the utilisation of a substantial research sample comprising nearly 11,000 manufacturing companies, accounting for the second most extensive research sample among the models outlined in Table 3. The dataset exhibited an imbalance, as only 700 out of the 11,000 companies were classified as bankrupt. The researchers employed the AUROC to assess the performance of the models. Additionally, they examined the quality of different training parameter configurations using a 10-fold cross-validation methodology for each model. Given the extensive number of ratios examined in the research, surpassing 60, it is noteworthy that the work of Durica et al. (2019a) encompasses the largest research sample among the Polish cases. The sample comprised nearly 29,000 companies operating across various sectors. CART and CHAID models were developed using classification trees (CT) as the structural basis. The receiver operating characteristic (ROC) curve was employed to evaluate the precision of the models at a level of accuracy of 98%. In contrast, the study conducted by Korol (2010b) offered the most extensive collection of models. The author developed a total of 52 models utilising seven distinct research methodologies, namely recurrent artificial neural network (SSN REC), one-way multi-layer artificial neural network (SSN MLP), artificial neural network based on genetic algorithms (SSN GA), artificial

neural network with radial basis functions (SSN RBF), self-organising map (SOM), SVM, and FL. The predictive accuracy of the best model was 94%.

It is noteworthy that the initial publications on models developed for the Polish economy were solely written in the native language. However, in subsequent years, particularly at the onset of the 21st century (Appenzeller, 2001), the authors commenced publishing articles in English. This corresponds to the proportion of articles written in Polish, which accounts for nearly 60%, while English content comprises only 40% of the articles. Furthermore, this is pertinent to the scholarly journals in which the articles were published. In Poland, the availability of English-language journals or Polish journals that permitted the publication of articles in English was limited. Over the course of time, an increasing number of these journals were established, with authors commencing to select not only local publication outlets but also international journals such as *International Advances in Economic Research* (Gruszczyński, 2004), *Economic Modelling* (Korol, 2013) or *Expert Systems with Applications* (Zięba et al., 2016). Nevertheless, a limited number of such works remain within the 40% corpus of English-language articles.

3.4 Analysis of Models in Slovakia

A total of 39 studies on bankruptcy prediction were evaluated, encompassing 160 models, as published by Slovak authors (Table 4).

Table 4. Bankruptcy prediction models constructed for the Slovak economy.

Model	No. of methods	Best method	Accuracy	Sample size	Period	Sector	No. of ratios	Selection criteria	No. of ratios in model
Chrastinová (1998)	1(1)	DA	96%	1,123	nd	AG	nd	nd	5
Zalai (2000)	1(2)	DA	nd	160	1994-1997	G	72	STW	8
Hladlovský and Král (2005)	1(1)	DA	87%	42	2002-2003	CH	24	EOM	7
Gavliak (2006)	3(3)	LR: GOM	93%	82	2002-2005	G	19	STW	5
Hladlovský and Král (2006)	2(2)	LR	97%	856	2002-2005	G	18	STW	nd
Král et al. (2007)	1(1)	FAA+DA	86%	190	2002-2004	G	36	FAA+STW	16
Boďa (2009)	1(4)	NN	94%	851	2002-2005	G	18	nd	18
Hurtošová (2009)	1(1)	LR	nd	427	2004-2006	G	85	MED, STW	4
Gurčík (2002)	1(1)	DA	nd	60	1998-2000	AG	35	EOM	5
Delina and Packová (2013)	1(4)	RA	21%	1,560	1993-2007	G	nd	COR	8
Harumová and Janisová (2014)	1(1)	LR	88%	53,206	2008-2011	G	20	STW	6
Boďa and Uradníček (2016)	1(4)	DA	71%	2,414	2009-2013	G	5	ALV	5
Gulka (2016)	1(1)	LR	79%	120,854	2012-2014	G	27	MISS, MCOL, STW	7
Mihalovič (2016)	2(2)	LR	69%	236	2013-2014	G	18	PT	5
Gavurová et al. (2017)	2(8)	CHAID	87%	1,182	2009-2014	G	102	STW	6
Horváthová and Mokrišová (2018)	1(1)	DEA	Nd	25	nd	TOU	12	ED	5
Kliestik et al. (2018)	1(4)	DA	83%	74,957	2012-2015	G	11	STW	6
Mihalovič (2018)	3(3)	GA	91%	1,280	2014-2017	G	58	STW	6
Valaskova et al. (2018)	1(1)	LR	Nd	62,533	2015	G	14	STW	9
Danišovská and Stachová (2019)	3(8)	REEM	82%	2,583	2009-2013	G	7	nd	nd
Gregova et al. (2020)	3(3)	NN	82%	64,757	2016-2018	G	14	STW	8
Horváthová and Mokrišová (2020)	2(2)	LR	95%	290	2016	NACE D	9	STW	5
Jenčová et al. (2020)	1(1)	LR	94%	856	2017	NFC, EEI	8	STW	5
Štefko et al. (2020)	2(2)	LR	87%	343	2016	HI	9	STW	7
Svabova et al. (2020)	2(3)	DA	94%	75,652	2016-2018	G	11	STW	nd
Horváthová et al. (2021)	2(2)	ANN	96%	444	2016	HI	11	none	11

Mazanec and Bartošová (2021)	1(1)	DA	91.50%	351	nd	NPO	14	STW	2
Štefko et al. (2021)	1(1)	DEA	Nd	343	2016	NACE D	17	nd	nd
Durica and Mazanec (2022)	3(3)	CART	88%	18,994		G	9	STW	nd
Gavurova et al. (2022)	2(2)	NN	100%	2,384	2018-2019	EEI	9	none	9
Mazanec et al. (2022)	1(1)	LR	97%	236	nd	NPO	14	STW	5
Svabova et al. (2022)	2(2)	DA	84%	88,252	2016	G	20	MCOL	6
Durica et al. (2023)	4(12)	BMLP	89%	75,649	2018-2019	G	25	MISS, MCOL	9
Horváthová et al. (2023)	1(1)	GTA	95%	186	2015-2021	C	5	DKA	5
Kanász et al. (2023)	6(18)	MTE	Nd	20,387	2013-2016	20 sectors	20	nd	nd
Mokrišová and Horváthová (2023)	2(2)	LASSO + LR + DEA	86%	1,349	nd	C	26	COR	7
Papík and Papíková (2023)	3(54)	LGBM	92%	106,407	2015-2019	G	46	none	46
Smorada et al. (2023)	1(1)	DA	72%	260	2013-2014	G	5	none	5
Valaskova et al. (2023)	1(5)	DA	89%	8,495	2020-2021	G	18	STW	7

Note: DKA - domain knowledge approach, EOM- test of equality of group means, MCOL – multicollinearity, MED median test, MISS - missing values, PT - pairwise testing.

Source: Chrastinová (1998), Zalai (2000), Hiadlovský and Král' (2005), Gavliak (2006), Hiadlovský and Král' (2006), Král' et al. (2007), Boďa (2009), Hurtošová (2009), Gurčík (2002), Delina and Packová (2013), Harumová and Janisová (2014), Boďa and Uradníček (2016), Gulka (2016), Mihalovič (2016), Gavurová et al. (2017), Horváthová and Mokrišová (2018), Klietík et al. (2018), Mihalovič (2018), Valaskova et al. (2018), Danišovská and Stachová (2019), Gregova et al. (2020), Horváthová and Mokrišová (2020), Jenčová et al. (2020), Štefko et al. (2020), Svabova et al. (2020), Horváthová et al. (2021), Mazanec and Bartošová (2021), Štefko et al. (2021), Durica and Mazanec (2022), Gavurova et al. (2022), Mazanec et al. (2022), Svabova et al. (2022), Durica et al. (2023), Horváthová et al. (2023), Kanász et al. (2023), Mokrišová and Horváthová (2023), Papík and Papíková (2023), Smorada et al. (2023), Valaskova et al. (2023).

Each of these studies includes at least one novel predictive model for the financial difficulties faced by Slovak enterprises. The studies encompass journal articles, conference papers, and final theses, guaranteeing extensive coverage of scholarly viewpoints and practical insights. We included the papers in scientific journals and some final theses or conference papers, as they have contributed significantly to the development of bankruptcy prediction in Slovakia. The first study is the final thesis by Chrastinová (1998), and it is among the most frequently cited papers in this domain in Slovakia.

The models developed for Slovakia employed various methods, with notable shifts in techniques over time. Initially, traditional statistical methods like MDA and LR were predominant; however, in recent years, there has been a noticeable increase in the application of advanced machine learning methods, such as NN and DT. Currently, MDA and LR methods remain frequently used, comprising almost 60% of the models, while machine learning techniques are increasingly popular, constituting around 25% of the models. This evolution highlights the growing preference for techniques that can manage complex data structures with improved predictive accuracy. Research on Slovak bankruptcy prediction models has predominantly been published in Slovak and Central European journals, indicating regional interest and proficiency in this field. A number of articles have been published in journals with elevated worldwide rankings, signifying the selective distribution of Slovak research to a wider audience. A portion of these publications is published in Slovak, mostly from the start of bankruptcy prediction in Slovakia; nonetheless, the bulk is accessible in English, indicating a steady yet continuous transition towards international accessibility.

The number of variables in the studies varied from 5 to 102, while in the final models, from 2 to 46 variables were used. Most frequently, the final models contain 5 or 6 variables. More than 60% of studies created universal prediction models for all sectors of the national economy.

3.5 Analysis of Models in the V4

The body of literature on the development of bankruptcy prediction or financial distress models specifically for the V4 is limited, resulting in only 8 articles being included in Table 5.

The inaugural publication focused on the V4, was released in 2013 and specifically detailed the application of data envelopment analysis (DEA). Comparative analysis was conducted between the results and statistical models (MDA, LR).

Table 5. Bankruptcy prediction models constructed for the V4 economy.

Model	No. of methods	Best method	Accuracy	Sample size	Period	Sector	No. of ratios	Selection criteria	No. of ratios in model
Vavrina et al. (2013)	3(3)	DEA	V4: 86%	2,652 V4	1998-2012	AG	9	ED	8-9
Režňáková and Karas (2014)	1 (1)	BT	SK, 93% CZ, 89%, PL, 71% HU, 86%	2,652 V4	2007-2012	M	14	COR	5
Kliestik et al. (2018)	1(5)	DA	SK, 83% CZ, 85%, PL, 88% HU, 82%, V4, 86%	105,708 SK; 62,794 CZ; 28,908 PL; 252,371 HU	2015-2016	G	37	STW	9-13
Durica et al. (2019b)	1(1)	LR	V4: 88%	30,892 SK; 25,159 CZ; 9,293 PL; 98,202 HU	2015-2016	G	37	LRT, RSC	17
Pavlicko et al. (2021)	4(4)	Ensemble RobustBoost CART	SK, 92% CZ, 94%, PL, 95% HU, 95%, V4, 94%	55,124 SK; 97,479 CZ; 68,267 PL; 346,712 HU	2016-2018	G	27	STW	7
Pavlicko and Mazanec (2022)	1(1)	LR	SK, 92% CZ, 93%, PL, 95% HU, 95%, V4, 94%	2017: 667,582 (109,509 failed)	2016-2018	G	27	MIN	2
Tomczak (2023)	2(32)	LR	SK, 94% CZ, 99%, PL, 91% HU, 92%, V4, 91%	1,500	2009-2018	C	69	K-S, t test, W-L, STW	2-7
Valaskova et al. (2023)	1(5)	DA	SK, 89% CZ, 93%, PL, 96% HU, 91%, For V4: 90%	8,495 SK; 8,073 CZ; 432 PL; 3,693 HU; V4: 20,693	2020-2021	G	18	STW	6-14

Note: BT – Boosted Trees, LRT – Likelihood ratio test, MIN – minimal set of predictors, RSC – R Square characteristics. Source: Vavrina et al. (2013), Režňáková and Karas (2014), Kliestik et al., (2018), Durica et al. (2019b), Pavlicko et al. (2021), Pavlicko and Mazanec (2022), Tomczak (2023), Valaskova et al. (2023).

Primarily, models were developed using statistical techniques, as only one article did not report a statistical model (Pavlicko et al., 2021). SM accounted for 90% of the 51 models developed for the V4. This proportion of SM usage is unequivocally distinct from what is observed in Czechia, Hungary, Poland, and Slovakia. The stepwise approach is the predominant criterion for indicator selection, closely resembling the analysis of individual countries. Two articles provide models specifically designed for the V4, without including the local models for each country within the group. Conversely, 5 articles exclusively addressed several industries, representing 31% of the constructed models. Significantly, in contrast to the individual V4 countries, there is a scarcity of articles pertaining to the entire Group, and these articles are exclusively written in English. Notably, these publications are mostly local and do not include publications from major publishers like Elsevier, Springer, or Wiley.

3.6 Literature Review of the Accuracy of Models from the V4

So far, multiple researchers have validated previously published bankruptcy prediction models. The aim of studying these verifications is to statistically assess and compare the accuracy of the developed models in each respective V4 country. The aim is to identify the models that most precisely assessed the financial condition of companies based on subsequent empirical research. The outcomes of validation for models one year preceding the bankruptcy declaration of enterprises are displayed in Tables 6, 7, 8, 9, and 10. A minimum of 100 companies were incorporated in the scope for the chosen studies, and the verification results were published in a scientific journal. The V4-level models have not yet been independently verified; hence, a thorough literature assessment for the whole V4 cannot be presented.

3.7 Literature Review of the Accuracy of Models in Czechia

Table 6 displays five studies evaluating the efficacy of four models. The smallest research sample comprises 273 firms, and the largest exceeds 2,600. The effectiveness of the models varies from 50% to 98%.

Table 6. Literature review of accuracy of models in Czechia.

Model	Author's Accuracy	Čámská, (2016)	Kuběnka et al. (2018)	Kuběnka and Myšková (2019)	Karas and Režňáková (2016)	Kuběnka et al. (2024)	Mean of accuracy
Sample		430	273	1,501	2,659	961	
Research period		2012	2009-2013	2012-2013	1999-2013	2016-2019	
Neumaier and Neumaierová (2001)	74%	98%					98%
Neumaier and Neumaierová (2005)	95%	98%			50%		74%
Karas and Režňáková (2013)	94%		62%	57-68%			62.00%
Kliestik et al. (2018)	85%					83%	83%

Source: Čámská (2016), Kuběnka et al. (2018), Kuběnka and Myšková (2019), Karas and Režňáková (2016), Kuběnka et al. (2024).

Two models were evaluated in two distinct investigations. Their outcomes varied substantially. Despite the IN01 model achieving a 98% accurate classification rate for a single study, its high efficacy remains unverified.

3.8 Literature Review of the Accuracy of Models in Hungary

Hungary is distinct as an exceptional case among the V4 countries. It quickly became evident that internationally recognised and widely utilised models yielded much inferior outcomes when applied in Hungary, as compared to their original performance and the insights gained from other nations. Consequently, Hungarian researchers neglected to undertake the task of verifying or conducting backtests on bankruptcy models developed in foreign countries. Furthermore, Hungarian models have not yet been validated by independent academic researchers (Table 7).

Table 7. Validation methods applied to the Hungarian models.

Author	Accuracy of the best model in the article	Compare the performance to other method(s) applied on the same database	Compare the performance to other model(s) developed on a different database	Validate the performance on a separated testing subsample via partitioning	N-fold cross-validation	Robustness check
Hajdu and Virág (2001)	82%	x				
Virág and Kristóf (2005)	86%	x		x		
Virág and Kristóf (2006)	87%	x		x		
Kristóf (2008)	84%	x		x		
Virág and Kristóf (2009)	94%					x
Bozsik (2011)	84%	x		x		
Kristóf and Virág (2012)	94%	x		x		
Virág and Nyitrai (2013)	89%	x		x	x	
Bareith et al. (2014)	85%			x	x	
Ékes and Koloszar (2014)	73%	x	x	x		
Nyitrai (2014a)	78%			x	x	
Nyitrai (2014b)	76%			x	x	
Virág and Nyitrai (2014a)	89%	x		x		
Virág and Nyitrai (2014b)	83%	x			x	
Felföldi-Szűcs (2015)	70%			x		
Nyitrai (2015)	80%			x	x	
Inzelt et al. (2016)	86%				x	x
Nyitrai (2017)	90%				x	
Nyitrai and Virág (2017b)	81%			x	x	
Nyitrai and Virág (2017a)	91%			x	x	x
Kristóf (2018)	82	x		x		
Nyitrai (2018)	91%					x
Sütő (2018)	83%	x				
Nyitrai (2019a)	89%				x	x

Nyitrai (2019b)	83%	x		x	x	
Nyitrai and Virág (2019)	87%	x	x		x	x
Szenes and Dabi (2020)	80%					x
Horváth (2021)	78%				x	x
Ágoston (2022)	84%	x		x	x	
Márton et al. (2023)	78%			x		
Szántó (2023)	86%			x		

Source: based on the references from Table 2.

The Hungarian models exhibited classification accuracies ranging from 70% to 94%. When evaluating the classification power of various models, it is crucial to take into account the research objectives and databases. It is important to assess the differences in classification abilities of the models, taking into consideration the definition of the explanatory and target variables used.

In Hungary, the predominant approach for model validation entails dividing the database into a training subsample and a testing subsample. Subsequently, performance validation was carried out on the testing sub-sample, comprising 20 cases and representing 64.5% of the publications. Model performance was evaluated by comparing it to other classification methods applied to the same database in 15 cases (48.4% of the articles). Alternatively, it was examined using n-fold cross-validation, specifically with 15 examples, which accounted for 48.4% of the articles. The models underwent validation through a robustness check in 8 instances, which represented 25.8% of the publications. Model performance was evaluated against other models created by different methods using a separate database in two publications, which constituted 6.5% of the total articles. Out of the total publications, 22 articles (71.0%) utilised at least two validation techniques.

3.9 Literature Review of the Accuracy of Models in Poland

Table 8 displays the findings of a comprehensive literature review conducted on the accuracy of enterprise declarations one year prior to bankruptcy. The efficacy analysis exclusively focuses on SM due to its universal applicability.

Table 8. Literature review of accuracy of models in Poland.

Model	Author's Accuracy	Antonowicz (2010)	Juszczuk and Balina (2014)	Kisielińska (2016)	Tomczak and Radosiński (2017)	Tomczak (2018)	Iwanowicz (2018)	Mean of accuracy
Sample Period		208 2003-2004	180 2009-2010	110 2009-2012	10,700 2000-2012 64%	1,353 2007-2012	139 nd 90%	- - 77.00%
Mączyńska (1994)	-							
Pogodzińska and Sojak (1995)	80%	61%	55%	60%				58.67%
Wierzbą (2000)	92%	92%	65%		66%		92%	78.75%
Appenzeller (2001)	94%	89%						89.00%
Hołda (2001)	92.50%	86%	50%	80%	58%		92%	73.20%
Appenzeller and Szarzec (2004)	88%		59.20%		66%	78%		67.73%
Gruszczyński (2004)	91%			82.30%				82.30%
Hamrol et al. (2004)	96%	94%	75.80%	82.70%	56%	75%	93%	79.42%
Wędzki (2005c)	78%	87%						87.00%
Mączyńska and Zawadzki (2006)	97%	95%	75.80%	82.70%	69%	67%	92%	80.25%

Source: Antonowicz (2010), Juszczuk and Balina (2014), Kisielińska (2016), Tomczak and Radosiński (2017), Tomczak (2018), Iwanowicz (2018).

Only six verification studies satisfy the research sample requirement of 100 companies for SM, while 43 verification studies meet the criteria for ML and AI models. This table displays a compilation of six studies, each comprising ten models that have been previously presented in the table. Merely two models, Hamrol et al. (2004) and Mączyńska and Zawadzki (2006), were validated across all conducted studies. The observed results exhibited a notable decrease in effectiveness compared to the effectiveness reported by the authors of the models. The mean verification scores for the two items were 79% and 80%, respectively. This phenomenon is particularly evident in considerable sample

sizes (Tomczak & Radosiński, 2017; Tomczak, 2018). This verification process revealed that these models might not be applicable to the manufacturing sector under consideration.

Evaluating the efficacy of ML and AI models poses significant challenges due to the absence of readily replicable and accurate data. An alternative approach to assess the efficacy of these models could involve utilising the identical database upon which researchers develop diverse ML and AI models. The online database containing the article Zięba et al. (2016) concerning Poland can be accessed at the following URL: <https://archive.ics.uci.edu/dataset/365/polish+companies+bankruptcy+data>. The publication occurred subsequent to the paper's printing, and numerous scholarly works employ it for research purposes. The dataset was also utilised in the Kaggle competition, accessible at the following URL: <https://www.kaggle.com/c/companiesbankruptcy-forecast/data>. The findings of the literature review pertaining to the utilisation of this database for constructing models are displayed in Table 9.

Table 9. Literature review of the Polish database.

Author	Accuracy of the best model in the article	Compare the performance to other method(s) applied on the same database	Compare the performance to other model(s) developed on a different database	Validate the performance on a separated testing subsample via partitioning	N-fold cross-validation	Robustness check
Paliński (2018)	97%	x		x		
García et al. (2019)	86%	x	x		x	
Pawełek (2019)	98%	x				
Wei et al. (2019)	97%	x	x	x		x
Wu et al. (2019)	97%	x		x		
Lahmiri et al. (2020)	95%	x	x		x	
Marso and El Merouani (2020)	92%	x		x		
Paliński (2020)	96%	x		x		
Uthayakumar et al. (2020)	98%	x	x		x	
Soui et al. (2020)	88%	x		x		
Smiti and Soui (2020)	96%	x		x		
Tsai (2020)	96%	x	x	x	x	
Zanka (2020)	81%	x		x		
Acharjya and Rath (2021)	98%	x		x		
Aljawazneh et al. (2021)	99%	x	x	x	x	
Al-Milli et al. (2021)	96%	x			x	
Dzik-Walczak and Odziemczyk (2021)	91%	x		x	x	
Jin et al. (2021)	69%	x	x	x	x	x
Muslim and Dasril (2021)	97%	x		x	x	
Yang et al. (2021)	98%	x	x	x	x	x
Yotsawat et al. (2021)	99%	x	x	x	x	
Zelenkov and Volodarskiy (2021)	87%	x	x		x	x
Zhang et al. (2021)	98%	x	x	x	x	x
Aly et al. (2022)	97%	x	x	x		
Elhoseny et al. (2022b)	99%	x	x	x		
Elhoseny et al. (2022a)	95%	x	x	x	x	
Hilal et al. (2022)	99%	x		x		
Kumar et al. (2022)	99%	x		x		
Repetto (2022)	83%	x		x		
Safi et al. (2022)	89%	x	x	x	x	x
Saipriya et al. (2022)	95%	x		x	x	
Vaiyapuri et al. (2022)	99%	x	x	x		
Adisa et al. (2023)	97%	x		x		
Islam and Mustafa (2023)	95%	x	x	x	x	
Ranjbaran et al. (2023)	98%	x	x	x	x	
Qian et al. (2023)	95%	x	x	x	x	
Van der Schraelen et al. (2023)	91%	x	x	x	x	
Ainan et al. (2024)	98%	x	x	x	x	x
Amirshahi and Lahmiri, (2024)	99%	x		x	x	x
Yang et al. (2024)	95%	x	x	x	x	
Chakraborty and Ranjan (2024)	95%	x		x		x
Dervovic et al. (2024)	93%	x	x	x	x	x

Source: Paliński (2018), García et al. (2019), Pawełek (2019), Wei et al. (2019), Wu et al. (2019), Lahmiri et al. (2020), Marso and El Merouani (2020), Paliński (2020), Uthayakumar et al. (2020), Soui et al. (2020), Smiti and Soui (2020), Tsai (2020), Zanka (2020), Acharjya and Rath (2021), Aljawazneh et al. (2021), Al-Milli et al. (2021), Dzik-Walczak, Odziemczyk (2021), Jin et al. (2021), Muslim and Dasril (2021), Yang et al. (2021), Yotsawat et al. (2021), Zelenkov and Volodarskiy (2021), Zhang et al. (2021), Aly et al. (2022), Elhoseny et al. (2022b), Elhoseny et al. (2022a), Hilal et al. (2022), Kumar et al. (2022), Repetto (2022), Safi et al. (2022), Saipriya et al. (2022), Vaiyapuri et al. (2022), Adisa et al. (2023), Islam and Mustafa (2023), Ranjbaran et al. (2023), Qian et al. (2023), Van der Schraelen et al. (2023), Ainan et al. (2024), Amirshahi and Lahmiri (2024), Yang et al. (2024), Chakraborty and Ranjan (2024), Dervovic et al. (2024).

Table 9 displays a total of 43 studies that utilised the aforementioned database. The predictive accuracy of the presented models falls within the range of 69% to 99%. The ensemble model, as proposed by Jin et al. (2021), achieved an accuracy rate of 69%. Furthermore, the models proposed by Aljawazneh et al. (2021), Yotsawat et al. (2021), Elhoseny et al. (2022b), and Amirshahi and Lahmiri (2024) demonstrated a classification accuracy of 99%. The mean efficacy of all studies is 94%, which closely approximates the target value of 96% obtained in the original studies. It is noteworthy to mention that a significant proportion of the works, approximately 55%, included the utilisation of diverse databases not only pertaining to Poland, as well as the development of models for these databases. The aforementioned databases encompassed various countries, including Australia, Finland, Japan, Germany, and Taiwan García et al. (2019). The models exhibited varying levels of accuracy.

3.10 Literature Review of the Accuracy of Models in Slovakia

Four studies conducted by Slovak authors concentrated on the validation of six previously developed Slovak models, utilising research samples that varied from tiny datasets of five firms to bigger samples of 27,029 and 3,329 enterprises (Table 10).

Table 10. Literature review of the accuracy of models in Slovakia.

Model	Author's Accuracy	Weissová (2017)	Weissova et al. (2016)	Kovacova et al. (2018)	Valaskova et al. (2020)	Mean of accuracy
Sample		5	5	27,029	3,329	
Research period		2011-2014	2014	2015	2016-2018	
Chrastinová (1998)	96%	40%	20%		87%	49%
Valaskova et al. (2018)	nd			94%		94%
Kliestik et al. (2018)	77%			29%	84%	56.00%
Kovacova and Kliestik (2017)	87%			90%		90%
Gurčík (2002)	nd				53%	53%

Source: Weissová, 2017; Weissova et al., 2016; Kovacova et al., 2018; Valaskova et al., 2020.

These validations evaluated models created throughout several timeframes, enabling a comparison between the models' predicted accuracy and actual results. The research, however, yielded inconclusive findings. For instance, whereas first models, like the inaugural Slovak model by Chrastinová (1998), had excellent accuracy (96%) as claimed by their developers, later validation tests indicated accuracy levels declining to 20-40% for some periods. Among the more recent models, the one by Valaskova et al. (2018) demonstrated higher validation accuracies, exceeding 93%.

3.11 Indicators Taken into Account in the Research and in the Models in Czechia

Figure 1 presents a succinct summary of the ratios evaluated in the research and models undertaken in Czechia.

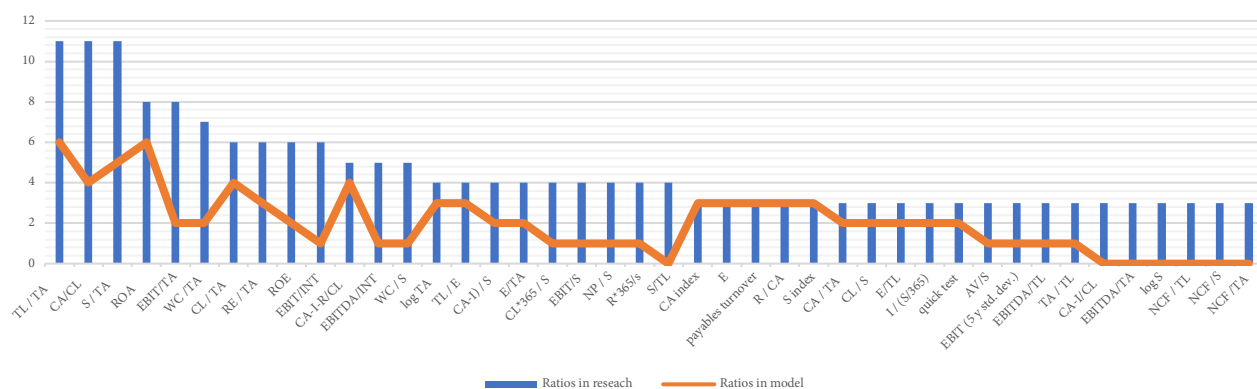


Figure 1. Indicators taken into account in the research in Czechia, 1990-2024.

Source: own calculations based on references from Table 1.

Note: AV- added value, CA – current assets, CL – current liabilities, E- equity, I- inventories, INT – interest, log – logarithm, NCF - net cash flow, NP – net profit, R- current receivables RE- retained earnings, S- net sales, TA – total assets, TL – total liabilities, WC – working capital.

It is important to note that not all studies provided the indicators utilised in the research, which may include Vochozka and Rowland (2015) and Vochozka et al. (2016). In the analysis of 21 studies, a total of 146 indicators were utilised, which were then reduced to 68 indicators incorporated in the models. In five studies, the indicators used a non-ratio format, predominantly reflecting size through the logarithm of total assets (Karas & Režňáková, 2013, 2017, 2018) and the 5-year standard deviation of EBIT as an indication of a multiperiod approach to variable definition (Karas & Režňáková, 2014). Additionally, Vochozka et al. (2015) implemented non-ratio indicators in the form of balance sheet components (such as equity, registered capital, or current liabilities) or profit and loss account elements (profit from ordinary operations).

The predominant category of financial ratios is solvency, including 32% of indicators, followed by profitability, which accounts for 22% of indicators. Solvency, profitability, liquidity, and activity metrics constitute 80% of the ratios analysed in models for Czech enterprises. The remaining 20% of ratios encompasses size variables, asset composition, debt structure, or cash flow configuration. The predominant solvency metric is the ratio of debt to total assets, which evaluates overall indebtedness; this has been utilised in eleven studies but only used in six models by various authors Dvořáček et al. (2012a), Dvořáček et al. (2012b), Valecký and Slivková (2012), Bemšet al. (2015), Němec and Pavlík (2016), Slaviček and Kuběnka (2016). Other frequently employed solvency ratios include debt to equity Jakubík & Teplý (2011), Karas & Režňáková (2014), Bemšet al. (2015) and current liabilities to total assets, which assess short-term indebtedness (Dvořáček et al., 2012a, 2012b; Karas & Režňáková, 2017, 2018). The predominant metric for assessing profitability is return on assets (ROA), which evaluates profitability from the standpoint of all stakeholders; this ratio was utilised in seven studies Neumaier and Neumaierová (2005); Valecký and Slivková (2012); Kalouda and Vaníček (2013); Slaviček and Kuběnka (2016); Karas and Režňáková (2018); Karas and Srbová (2019). In contrast, profitability from the shareholders' perspective (i.e., ROE) is seldom observed in models for Czech enterprises, as noted exclusively in Jakubík and Teplý (2011). The most commonly utilised metric for liquidity is the CR as referenced by Neumaier and Neumaierová (2005); Kalouda and Vaníček (2013); Bemšet al. (2015); Němec and Pavlík (2016). This contrasts with the prevailing tendency in bankruptcy prediction models, which favour Altman's working capital above total assets, as utilised in models for Czech enterprises in study of Vochozka et al. (2015) and Karas and Režňáková (2018). The primary focus of activity ratios is the overall evaluation of total asset usage, measured by the ratio of sales to total assets, known as total asset turnover Neumaier and Neumaierová (2005), Dvořáček et al. (2012a), Dvořáček et al. (2012b), Karas and Režňáková (2013), Machek et al. (2015). Particular emphasis was placed on inventory turnover (sales relative to inventory) or, more specifically, days sales in inventory.

3.12 Indicators Taken into Account in the Research and in the Models in Hungary

Despite extensive model development efforts, numerous significant relationships have been discovered in the decades-long history of bankruptcy prediction. However, there is still no consensus on which explanatory variables are most effective in predicting corporate failure in Hungary. The extensive variety of classification methods, combined with the diverse modelling databases from various environments, industries, and time periods, poses a significant challenge in formulating hypotheses about the causes of corporate failure and the mechanisms behind it.

In Hungary, there were 107 indicators that were considered as potential model variables in the 31 models that were referred to. The primary financial indicators used as input variables in bankruptcy modelling are based on well-established liquidity, profitability, indebtedness, leverage, turnover, cash flow, and size ratios commonly used in the field of corporate finance (Figure 2).

Furthermore, the relation of liquid assets to different balance sheet items, as well as the coverage of certain balance sheet or profit and loss items by net revenue, was also widespread in Hungary. Noncorporate financial ratios, such as macroeconomic indicators, market indexes, qualitative characteristics of companies, and loan repayment behaviour, were used less frequently. A total of 84 indicators were chosen as significant input variables in at least one distinct Hungarian bankruptcy

model. The key financial ratios used in published models to predict corporate bankruptcy in Hungary include the CR, liquidity quick ratio (QR), proportion of liquid assets to current assets, cash flow to liabilities ratio, ROA, return on sales (ROS), equity ratio (ER), indebtedness ratio, working capital to total assets ratio, leverage ratio, total turnover ratio, inventory turnover ratio, and the natural logarithm of total assets and/or total sales.

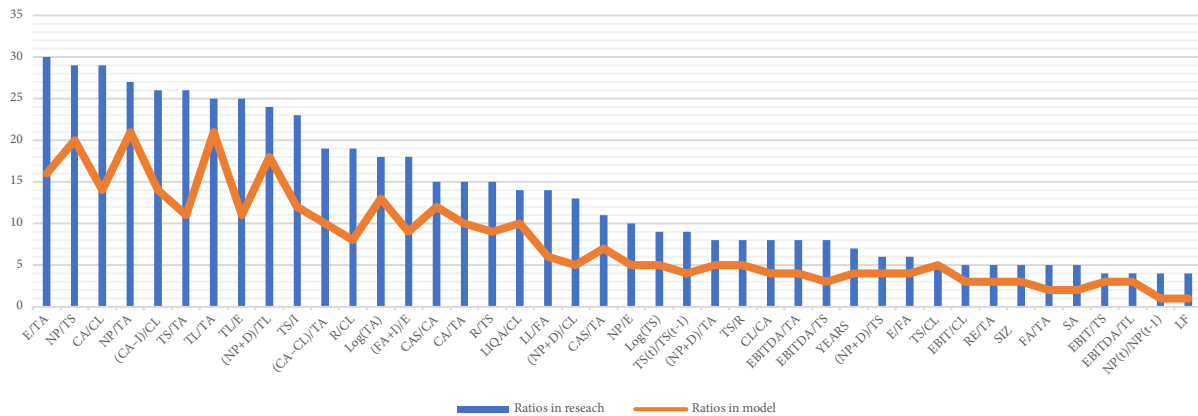


Figure 2. Indicators taken into account in the research in Hungary, 1990-2024.

Source: own calculations based on references from Table 2.

Note: D – depreciation and amortisation, FA – fixed assets, LF – Legal form, LL – Long-term liabilities, CAS – cash, SA – Sector of activity, SIZ – company size category, TS – total sales, YEARS – number of observed years in the database.

3.13 Indicators Taken into Account in the Research and in the Models in Poland

Figure 3 provides a concise overview of the ratios that were considered in the research and models conducted in Poland. A total of approximately 250 indicators were employed in the conducted studies, whereas the models ultimately yielded a reduction to 140 indicators, representing a decrease of over 100. The presented indicators can be classified into 10 different groups: liquidity (12 ratios), solvency (45 ratios), profitability (50 ratios), turnover (42 ratios), market position (24 ratios), dynamics (15 ratios), cash flow (13 ratios), sector indicators (25 ratios), company size (3 ratios) and others (12 ratios). The most substantial category comprises indicators related to profitability, while the least extensive category comprises indicators pertaining to enterprise size. It is important to acknowledge that certain studies did not achieve the precise determination of the indicator formula. In certain cases, the number of indicators initially considered was provided without including their respective formulas, while in other instances, only their names were provided.

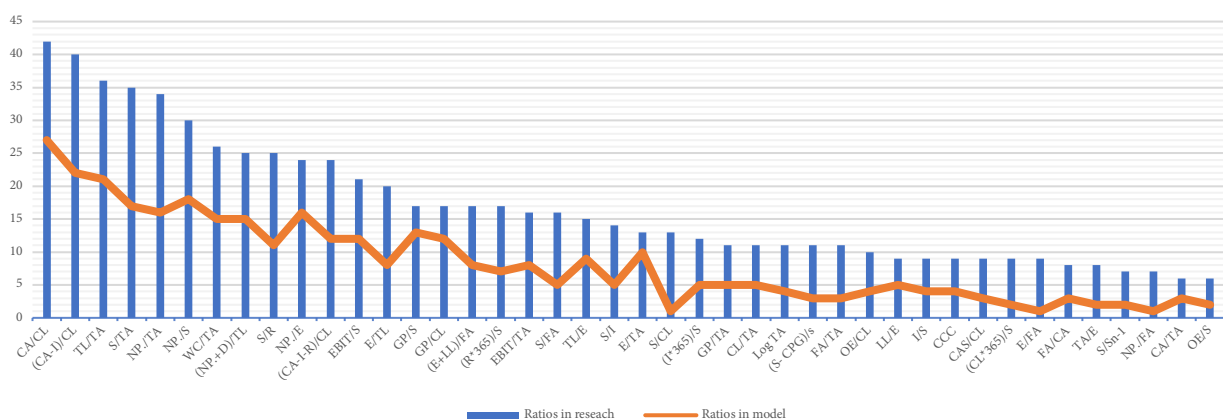


Figure 3. Indicators taken into account in the research in Poland, 1990-2024.

Source: own calculations based on references from Table 3.

Note: CCC - cash conversion cycle, CPG - cost of products, goods and materials sold, GP – gross profit, OE - operational expenses.

Upon examination of the frequency distribution of individual indicators within the studies, it is noteworthy that two liquidity indicators, namely CR and QR, exhibit a distinguished presence, appearing in more than 87% and 82% of the studies, respectively. Two additional liquidity indicators, namely the amount of working capital (in 53% of studies) and the cash ratio (in 49% of studies), are among the top 10 most commonly utilised indicators in research. In conjunction with liquidity ratios, there exist two indicators pertaining to leverage, namely debt and the coverage of total liabilities with the financial surplus ratio. Additionally, profitability indicators such as ROA and ROS are considered, alongside turnover indicators encompassing revenue and receivables turnover ratio. In contrast, the top 10 indicators commonly employed in models closely align with the top 10 indicators cited in research. The predominant liquidity indicators in the models are the CR and QR, although their frequency has decreased to 55% and 45% respectively. The process of selecting indicators resulted in a significant reduction in the frequency of occurrence for each individual indicator. It is noteworthy to mention that a significant proportion, specifically over 80%, of the indicators incorporated in the models exhibit a low frequency, with a maximum rate of 1%.

3.14 Indicators Taken into Account in the Research and in the Models in Slovakia

In the analysed Slovak studies, 156 distinct variables, primarily financial ratios, were employed. The TL/TA ratio was the most commonly utilised, serving as a possible predictor in 28 research (Figure 4), of which 20 (about 71%) identified it as a significant variable in the developed models. The second position is held by the ratio TL/E utilised in 26 studies, with 20 (63%) of them using this ratio as significant in the final model. The third most frequently used variable was EBIT/INT, included in 18 studies, although deemed significant in just 8 (almost 44% of the total). Of all the ratios, 64 were utilised just once.

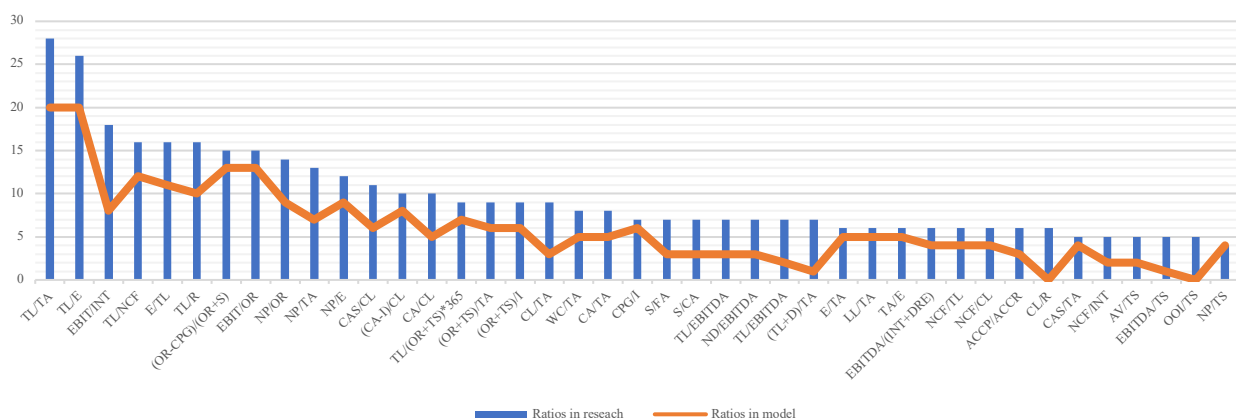


Figure 4. Indicators taken into account in the research in Slovakia, 1990-2024.

Source: own calculations based on references from Table 4.

Note: ACCP – accounts payable, ACCR – accounts receivable, DRE – deferred revenue, ND – net debt, OR – operating revenues, OOI other operating income.

3.15 Indicators Taken into Account in the Research and in the Models in the V4

When comparing the ratios examined in different countries, it is evident that there are fewer ratios relevant to the V4 (Figure 5).

This can be attributed to the limited number of publications specifically addressing the V4. The studies were conducted using a total of 91 indicators, out of which 61 were included in the models. The indicators were categorised into 8 out of the 10 previously discussed groups due to the absence of representatives for the market position and sector indicators group. The most extensive category comprises profitability and solvency indicators, each featuring 23 ratios. Conversely, the smallest category comprises company size indicators, each consisting of two ratios. An examination of all indicators revealed that only two are consistent across all studies: ROA and debt ratio (DR). However, only the DR was incorporated into the statistical models. Ratios such as CR, QR, ROA, ROS, current

liabilities to total assets, and revenue turnover ratio are presented in six studies, accounting for 86% of the studies. However, these ratios are no longer included in models with such frequency. Consistently, studies and models tend to employ identical indicators. Furthermore, it is noteworthy to mention that the majority of the indicators in studies and models are present only once, namely 58% and 73%, respectively.

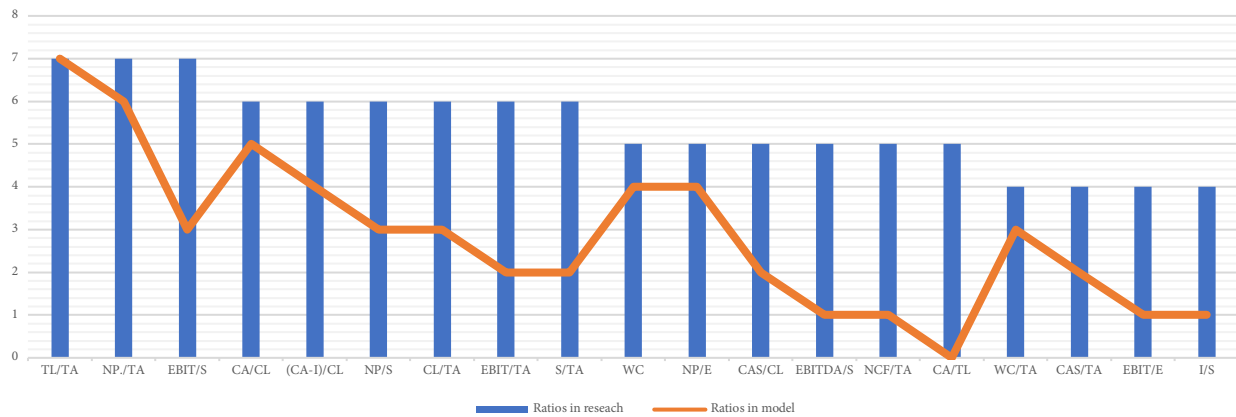


Figure 5. Indicators taken into account in the research in the V4, 1990-2024.

Source: own calculations based on references from Table 5.

3.16 The Most Frequently Used Methods to Construct Bankruptcy Prediction Models

Tables 11, 12, 13, 14, and 15 enumerate the methods employed in individual countries and across the V4. An examination of the tables reveals a progressive increase in the number of models developed over the years.

Table 11. The most frequently used methods to construct bankruptcy prediction models in Czechia with the year of publication.

Years—Methods	DA	LR	DT	NN	RF	XGB	SVM	GA	Others	Total
1990	0	0	0	0		0	0	0	0	0
2000	3	0	0	0	0	0	0	0	0	3
2010	19	16	5	19	1	0	1	0	6	67
2020	0	1	1	0	0	0	0	0	1	3
Total	22	17	6	19	1	0	1	0	7	73

Source: own calculations based on references from Table 1.

The early 1990s exhibited a scarcity of models, whereas the 2010s marked a substantial proliferation of models within individual countries and for the entire V4. It is unequivocally evident that discriminant analysis was the predominant method for model construction, with Hungary exemplifying the frequent application of logit analysis. Additionally, methodologies rooted in artificial intelligence and machine learning experienced significant prominence during the 2010s. A review of the summary data depicted in Figure 6 indicates that discriminant analysis and logit analyses were the most utilised methods, with neural networks occupying the third position. This part answers the first research question. There are many methods applied to predict the bankruptcy of companies within the V4, but mostly statistical methods are used.

Table 12. The most frequently used methods to construct bankruptcy prediction models in Hungary with the year of publication.

Years—Methods	DA	LR	DT	NN	RF	XGB	SVM	GA	Others	Total
1990	0	0	0	0	0	0	0	0	0	0
2000	5	7	2	5	0	0	0	0	0	19
2010	11	36	25	11	0	0	1	0	8	92
2020	0	5	0	1	1	0	2	0	1	10
Total	16	48	27	17	1	0	3	0	9	121

Source: own calculations based on references from Table 2.

Table 13. The most frequently used methods to construct bankruptcy prediction models in Poland with the year of publication.

Years—Methods	DA	LR	DT	NN	RF	XGB	SVM	GA	Others	Total
1990	5	0	0	0	0	0	0	0	0	5
2000	22	26	0	0	0	0	0	0	0	48
2010	35	38	16	36	15	1	31	8	68	248
2020	23	9	8	8	0	0	1	1	1	51
Total	85	73	24	44	15	1	32	9	69	352

Source: own calculations based on references from Table 3.

Table 14. The most frequently used methods to construct bankruptcy prediction models in Slovakia with the year of publication.

Years—Methods	DA	LR	DT	NN	RF	XGB	SVM	GA	Others	Total
1990	1	0	0	0	0	0	0	0	0	1
2000	6	3	0	4	0	0	0	0	1	14
2010	19	4	4	1	0	0	0	1	9	38
2020	11	9	12	6	1	18	3	0	47	107
Total	37	16	16	11	1	18	3	1	57	160

Source: own calculations based on references from Table 4.

Table 15. The most frequently used methods to construct bankruptcy prediction models for the whole V4.

Years—Methods	DA	LR	DT	NN	RF	XGB	SVM	GA	Others	Total
1990	0	0	0	0	0	0	0	0	0	0
2000	0	0	0	0	0	0	0	0	0	0
2010	6	2	1	0	0	0	0	0	1	10
2020	21	17	1	1	0	0	0	0	2	42
Total	27	19	2	1	0	0	0	0	3	52

Source: own calculations based on references from Table 5.

3.17 The Accuracy of Models Based on the Literature Review for the V4 countries

Table 16 presents an overview of the accuracy of models for individual countries in the V4. It is important to clarify that DA, LR, and NN denote the mean accuracy of all published models for a particular method as assessed by the model authors, whereas DA L signifies the mean accuracy of all models verified by independent researchers.

Table 16. The accuracy of bankruptcy prediction models for the most frequently used methods in V4.

Country Method	DA	DA L	LR	NN	ML
Czech Republic	86%	79%	87%	95%	-
Hungary	86%	-	84%	84%	84%
Poland	90%	77%	85%	92%	94%
Slovakia	79%	68%	89%	92%	-

Source: own calculations based on references from Tables 1-10.

Consequently, ML denotes the mean accuracy of machine learning models utilising the public database for Poland and the mean accuracy of machine learning models for Hungary (Table 2). Upon analysing the table, it can be concluded that models employing machine learning techniques have the best accuracy. The highest accuracy of methods is achieved by light gradient boosting machine (LightGBM) as well as extreme gradient boosting (XGBoost) in the case of Poland, and neural networks in the case of Hungary. It is important to remember that discriminant analysis models validated by researchers exhibit lower accuracy than that claimed by their developers. Conversely, for models employing machine learning, either the same results or superior outcomes were achieved compared to those reported by the model developers. It is important to acknowledge that machine learning models cannot be replicated identically due to their black box nature, unlike statistical approaches. This statement answers the second and third research questions (Figure 6).

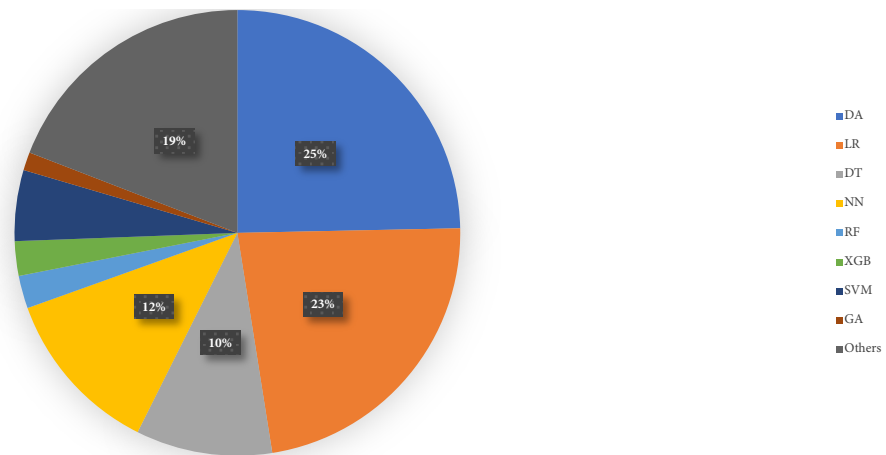


Figure 6. The most frequently used methods to construct bankruptcy prediction models in the V4, 1990-2024.

Source: own calculations based on references from Table 1-5.

The accuracy of the models was tested, but mainly for statistical models, except for Hungary, where independent researchers did not verify the existing models. The researchers demonstrate that statistical models are less accurate than their authors claim. Moreover, in the case of Poland, the accuracy was also tested for machine learning methods, because there are public databases. The results show that models employing machine learning techniques have the best accuracy.

3.18 The Most Frequently Used Indicators in Models and Research in the V4

Table 17 illustrates the most often utilised indicators in research and models for the whole V4. It is noteworthy that only a limited number of variables are consistently seen across individual countries.

Table 17. The most frequently used ratios in the V4.

Ratios	Number of occurrences in studies	Number of occurrences in models	Percentage of occurrences in studies	Percentage of occurrences in models
TL / TA	107	75	73%	51%
CA/CL	98	55	67%	37%
(CA-I)/CL	82	48	56%	33%
NP/TA	81	50	55%	34%
E/TA	53	33	36%	22%
NP/E	51	34	35%	23%

Source: own calculations based on references from Tables 1-5.

The dominant indicators in the V4 are two indicators from three groups: debt ratios (DR, ER), liquidity ratios (CR, QR) and profitability ratios (ROA, ROE). In comparisons across particular countries, it is futile to seek non-financial indicators (apart from the company size quantified by the logarithm of assets) or macroeconomic indicators, owing to their infrequent application in research and models. This pertains to the tendency of model developers to utilise prevalent indicators already employed in other models, particularly evident during the initial phases of model development, which drew inspiration from "Western models". Then, for the ratios specified in Table 17, nonparametric ANOVA was used to identify differences in the values between countries. Table 18 presents the results of nonparametric ANOVA in the period 2006-2021.

Table 18. Results of non-parametric ANOVA.

Year Ratio	Current ratio	Quick ratio	ROA	ROE	Debt ratio	Equity ratio
2006	CZ-SK, CZ-HU, CZ-PL, HU-PL no	only SK-PL yes	all yes	all yes	CZ-HU, CZ-PL no	CZ-HU, CZ-PL no
2007	CZ-HU, CZ-PL no	CZ-HU, CZ-PL, SK-HU no	all yes	all yes	CZ-HU, CZ-PL, HU-PL no	CZ-HU, CZ-PL, HU-PL no
2008	CZ-PL no	SK-HU no	CZ-HU, CZ-PL no	CZ-HU no	CZ-HU, CZ-PL no	CZ-HU, CZ-PL no

2009	CZ-PL no	SK-HU no	CZ-PL no	CZ-SK, HU-PL	CZ-PL no	CZ-PL no
2010	all yes	all yes	only CZ-HU yes	CZ-SK, SK-HU, SK- PL no	all yes	all yes
2011	HU-PL no	SK-HU no	CZ-SK, SK-PL no	CZ-SK no, HU-PL no	SK-PL no	SK-PL no
2012	HU-PL no	all yes	CZ-PL, SK-PL no	CZ-SK no	all yes	all yes
2013	HU-PL no	all yes	CZ-PL no	CZ-SK no	all yes	all yes
2014	all yes	all yes	all yes	CZ-SK no	HU-PL no	all yes
2015	all yes	all yes	SK-PL no	CZ-SK, CZ-PL no	all yes	all yes
2016	all yes	HU-PL no	all yes	HU-PL no	all yes	all yes
2017	CZ-HU no	all yes	all yes	SK-HU no	all yes	all yes
2018	CZ-HU no	all yes	all yes	all yes	all yes	all yes
2019	CZ-HU no	all yes	CZ-PL	all yes	all yes	all yes
2020	CZ-HU no	all yes	all yes	CZ-SK no	all yes	all yes
2021	CZ-HU no	all yes	all yes	all yes	all yes	all yes

Source: own calculations.

Of the 6 indicators, the values of debt ratios (DR, ER) differ most frequently in the research period between countries, and these differences are statistically significant (all yes) with some exceptions at the beginning of the period (CZ-HU, CZ-PL, HU-PL no). For the remaining indicators, the differences are not so statistically significant because there are more inclusions, i.e. these differences are not significant among all V4 countries. In the absence of differences in indicator values between countries, there is a basis for building models for the entire V4. This part is an answer to the fifth research question.

3.19 The Number of Ratios Frequently Used in Models in the V4

Upon examining the different models within the V4 regarding the quantity of indicators incorporated, it is evident that this amount fluctuates between 3 and 8 variables, as seen in the summary in Figure 7.

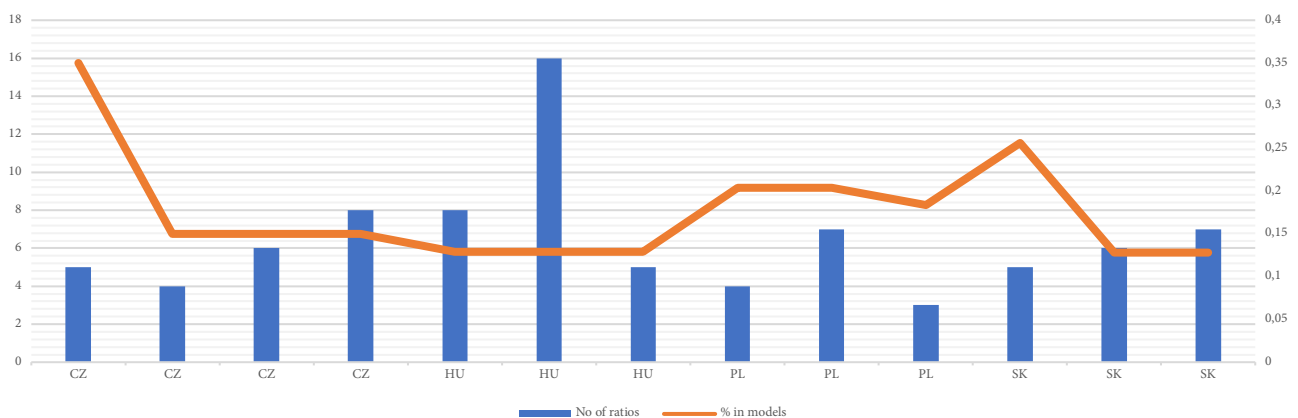


Figure 7. The number of ratios frequently used in models in the V4.

Source: own calculations based on references from Table 1-5.

Some models incorporate more factors; however, these models typically rely on machine learning techniques, as exemplified by Hungary. In this instance, five, eight, and sixteen indicators are present in the models, all corresponding to the identical frequency of occurrence, namely 13%. Conversely, for the other V4 countries, this figure does not surpass 7 indicators, but the frequency of occurrence varies. In the models, five variables are present in 35% of Czech works, 26% of Slovak works, and less than 18% of Polish works, therefore, failing to rank among the top three. Furthermore, the subsequent quantity of indicators ex aequo is 4 indicators and 7 indicators in Poland, which pertains to 20% of works, however, in Czechia, it accounts for 15% for the number 4 and 13% for the number 7. Another statistic present in the models is 3, representing 18% of the works related to the Polish economy. It is noteworthy that it occurs alone for this country, whereas it does not for the others. Furthermore, the

primary approach for variable selection in each country is stepwise. This part answers the fourth research question. Models are usually constructed based on three to eight variables.

3.20 The Research Samples Used in the Studies Across the V4

The quantity of research samples varies considerably across different countries (Figure 8). The highest number of analysed works is in Poland; nonetheless, these works employed limited research samples. As the sample size increased, the proportion of works markedly diminished.

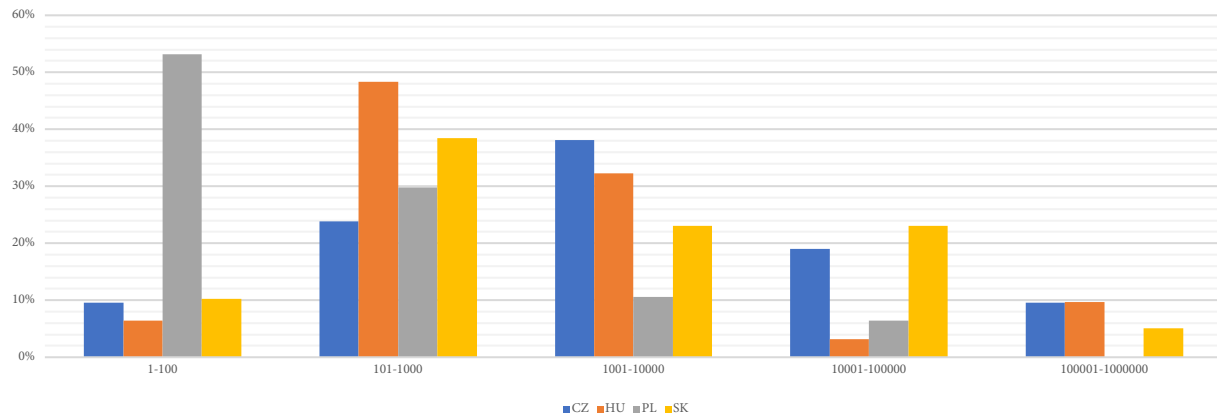


Figure 8. The research samples used in the models within the V4.

Source: own calculations based on references from Table 1-5.

For instance, 53% of the studies had research samples that did not surpass 100 firms, 30% had samples that did not exceed 1,000 enterprises, and 11% had samples that did not exceed 10,000 enterprises. Conversely, for 6%, the research sample did not surpass 100,000 firms. It is important to highlight that these figures are at the lower end of the spectrum, despite the fact that Poland has the highest number of operating enterprises within the V4. The greatest research samples are notably from Hungary, Czechia, and Slovakia, respectively. The largest sample for Hungary comprises 368,328 firms, for Czechia 241,380 enterprises, and for Slovakia 120,854 enterprises. In the largest sample size category of these countries, Hungary has three works, while Czechia and Slovakia each have two. It is worth adding that all the works using research samples exceeding 100,000 enterprises focused exclusively on statistical methods (MDA, LR), with the exception of one work from Slovakia. This section answers the seventh research question. Most of the research samples do not exceed 1,000 companies, except for Poland (most of the research samples are in the range of 1-100) and the Czech Republic (most of the research samples are in the range of 101-10,000).

3.21 The Number of Articles in Top Journals in which Research on Individual V4 Countries was Published

Numerous journals exist that publish research from the V4 countries. Nonetheless, several publications are of local significance, particularly when journals disseminate articles in the local language. Conversely, local journals publishing in English possess a broader scope, and in recent years, their numbers have increased, along with the volume of scholars publishing in English. It is worth noting that the majority of globally published research on bankruptcy prediction models, indexed in prestigious journals, is associated with the Elsevier publishing house (Dasilas & Rigani, 2024). In comparison to publications from the V4 countries, it is evident that only five papers were published by this publishing house, as seen in Figure 9.

Every country, except Hungary, has published one paper in Expert Systems with Applications. One study was published in Economic Modelling from Poland, and another in Socio-Economic Planning Sciences from Hungary. This part answers the last question. In most cases, the works are published in local journals with a few exceptions, such as Expert Systems with Applications.

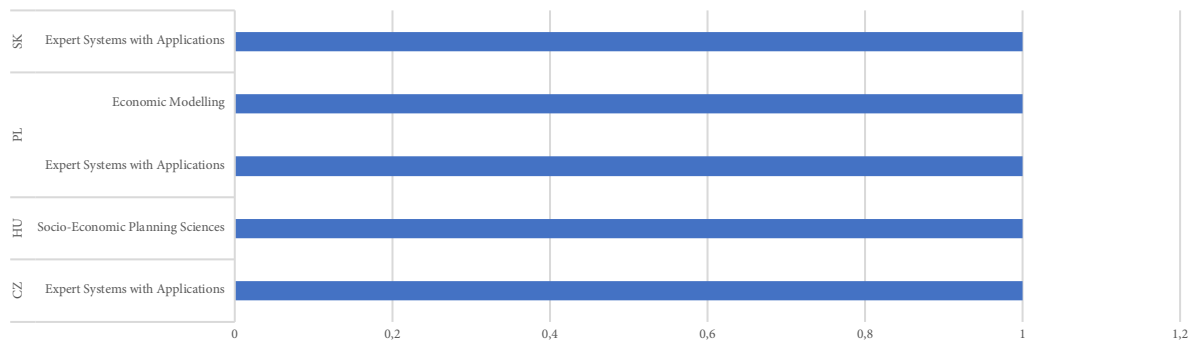


Figure 9. The top journals in which research on individual V4 countries was published.

Source: own calculations based on references from Table 1-5.

3.22 Upcoming Trends in Bankruptcy Prediction for the V4

The results suggest an increased adoption of artificial intelligence methodologies. There is a noticeable rise in the application of these approaches; yet, their prevalence remains limited. This growth is expected to transpire, particularly when considering the dissemination of databases in public repositories from the relevant countries addressed in this article. The sharing of data will enhance researchers' interest in the V4 analysis; for instance, the database for Polish enterprises is often utilised (Fig. 7). The majority of models were developed primarily using financial indicators, with a minor inclusion of non-financial indicators and no use of text analysis to assess the utility of off-balance sheet information on the firm. Off-balance sheet information may encompass news articles and social media posts. To date, no similar endeavour has been undertaken in the V4 countries. Furthermore, an increasing number of studies have to be published in esteemed journals to enhance interest in the analysis of the V4 countries and other Central and Eastern European nations.

4. Discussion

The research comprehensively examines the research focused on developing bankruptcy prediction models for specific countries and the whole V4. The investigations revealed that the predominant methods employed were discriminant analysis and logit analysis, with neural networks ranking third. In comparison to general global reviews, the findings are analogous (Bellovary et al., 2007), with the distinction being the reduced application of neural networks and machine learning techniques in the V4. It seems distinct in comparison to Alaka et al. (2018), where the increased utilisation of machine learning techniques is evidently apparent. The application of machine learning techniques is far less prevalent than in developed economies (Ahmed et al., 2022). Furthermore, when juxtaposing the results with those aggregated for the V4, the proportion of statistical models in the research is much less in contrast to Kovacova et al. (2019). It is noteworthy that the study of Kovacova et al. (2019) examined 103 models, whereas our article studied 147 models. The analysis predominantly focused on the Polish studies, as 61% of them originated from Poland. We have included a higher number of studies from Hungary (five times more) and Slovakia (three and a half times more), which also impacted the outcome. The amounts of contributions from individual countries in our work are more comparable; hence, the values utilised in one country do not substantially influence the outcome, unlike in Kovacova et al. (2019). An investigation of the evaluation of the Hungarian article Kristóf and Virág (2020), reveals a significant prevalence of logit analysis and neural networks. This substantially affects the outcome of the comparison of the approaches employed in the review.

It is noteworthy that, to date, no efforts have been undertaken in Hungary to publish the validation of any previously constructed models by independent academic researchers. Among the V4 nations, this is the sole country where no model validation corroborated the efficacy of models presented by

their developers. Models based on machine learning have the best accuracy, which is unsurprising. Furthermore, for Poland, further verification was conducted due to its status as a publicly accessible resource, frequently utilised for developing models employing artificial intelligence and machine learning techniques. The efficacy achieved by other authors averages 94% over 43 publications, which is a commendable outcome. Furthermore, the accuracy of discriminant analysis models is much inferior to the figures reported by their authors, ranging from 68% to 79%. The average accuracy values for discriminant analysis are comparable to those in Alaka et al. (2018), but the results for neural networks and logistic regression are superior. The authored works have often been published by local publication outlets, and over time, they have started to be published in English. Only a limited number of journal articles were published by top publishing houses.

The number of indicators incorporated in the models across the V4 fluctuates between 3 and 8. In the models, five indicators are present in 35% of Czech works, 26% of Slovak works, and less than 18% in Poland and Hungary. In comparison to Kovacova et al. (2019), five indicators rank second. The leading position is occupied by employing four variables, which have a utilisation rate of 29%. Furthermore, the primary approach for selecting indicators for models in each of the examined countries is stepwise. This is the preferred approach for constructing statistical models (Alaka et al., 2018), and the majority were developed using these approaches in the V4. The majority of the studies utilise research samples of up to 1,000 firms, consistent with the studies conducted in other countries (Kumar & Ravi, 2007; Alaka et al., 2018; Dasilas & Rigani, 2024). The smallest samples are created for Poland, barely surpassing 30,000, whilst the largest samples are for Hungary, far over 100,000.

It is worth pointing out that the obtained results are different from those presented by Tomczak (2021). In those studies, there are no mean differences between the values of ratios in the groups for debt indicators (DR, ER). The work compared differences between only sectors and not countries for stock companies.

In comparing the results to prior review studies, it is important to note that not all give a model analysis; some only identify the authors for each country (Kral et al., 2018; Prusak, 2018), while others concentrate on various features, such as the results of bibliometric analysis (Prusak & Karas, 2024; Ahmed et al., 2022). However, these studies possess several limitations. They exclusively encompass publications related to Poland and Hungary, thus diminishing the quantity of studied works. Simultaneously, this limitation mitigates the influence of numerous works in the comparative analysis for the whole V4. Although the study offers a comprehensive insight into bankruptcy prediction models for the V4 countries, its findings may be generalised to regions or countries with differing economic conditions only after careful consideration. However, we consider the study valuable also for international readers who want to understand better the development and application of prediction models in emerging market conditions. Another possible weakness of the study is that the models reviewed are drawn from multiple sectors, and the reviewed models were created using various methodologies and data sources. This heterogeneity could affect the generalizability of the conclusions. Nevertheless, by examining a wide range of models, the study highlights universal predictors and methodological trends, which can be valuable for future research and the prediction of the companies' financial state development. A different limitation of the work is the lack of precise specification of all indicators taken into account in the research in some works, and the assumption that only the name of the indicator is given, without its formula. This is due to the fact that in some works it is not specified which indicators were taken into account in the research, only it is written, e.g. the number of indicators taken into account in the research is 100. On the other hand, in some works only the names of the indicators are given, e.g. ROA, ROE, without specifying whether the numerator should be gross, net profit or maybe EBIT.

Conclusions

The article examines several corporate bankruptcy prediction models developed for specific countries and the whole V4 from Q1 1990 to Q1 2024. The review encompasses an evaluation of the

works, considering the chronology of their creation, the sample size, the diversity of methodologies and best methods employed in various studies, classification accuracy, research period, the number of indicators in the studies and models, the sector analysed, and the variable selection techniques utilised for model development. The review considers 21 papers for Czechia, 31 for Hungary, 49 for Poland, 39 for Slovakia, and 7 for the entire V4. Furthermore, 43 papers pertaining to Poland were examined to assess the accuracy of machine learning methodologies used to study samples sourced from open databases of a particular nation. To a certain extent, the accuracy of statistical models was validated by an analysis of model correctness performed by independent researchers. The accuracy of enterprise classification by statistical models is considerably inferior to that exhibited in the authors' research. Conversely, models utilising machine learning exhibit superior accuracy via independent validation. Notwithstanding this, the predominant techniques employed within the V4 are statistical ones.

The quantity of research samples varies considerably across different countries and the majority of the studies utilise research samples of up to 1,000 firms. It should be pointed out that all the works using research samples exceeding 100,000 enterprises focused exclusively on statistical methods (MDA, LR) except one work from Slovakia and did not consider machine learning-based methods.

The article delineates the indicators considered in the research and those employed to develop the models. The research considered a varying number of indicators for each country: Czechia had 146, Hungary 107, Poland 250, Slovakia 156, and for the V4-level research, it was 91. Nevertheless, only a limited number of variables are consistently observed across countries with comparable frequency. The predominant ratios in the V4 are the total debt ratio, equity ratio, the current liquidity ratio, quick ratio, return on equity and the return on assets. But the differences in values between countries are statistically significant for debt indicators, but not so much for the others. In the absence of differences in indicator values between countries, there is a basis for building models for the entire V4.

In examining other commonalities among nations, it is important to note that non-financial or macroeconomic variables are often absent from the most often utilised metrics, owing to their infrequent application in research and models. This pertains to the observation that, in several instances, model developers employ a shared array of variables already utilised in other models.

In conclusion, the models have predominantly been constructed using financial indicators; however, there has been no effort to employ text analysis to determine the utility of off-balance sheet information on companies operating in the V4. Off-balance sheet information might encompass news articles and social media posts. This might be an emerging trend in the development of financial distress models in the V4. The research findings ought to be disseminated in prestigious journals, as there have been limited publications on the V4 in leading journals to date.

Author Contributions: S.K.T: Conceptualization, Methodology, Formal analysis, Funding acquisition, Investigation, Project administration, Resources, Supervision, Validation, Visualization, Writing – Original draft, Writing – Reviewing and Editing. MK: Formal analysis, Resources, Validation, Writing – Original draft, Writing – Reviewing and Editing. T.K.: Formal analysis, Resources, Validation, Writing – Original draft, Writing – Reviewing and Editing. L.D.: Formal analysis, Resources, Validation, Writing – Original draft, Writing – Reviewing and Editing. M.D.: Formal analysis, Resources, Validation, Writing – Original draft, Writing – Reviewing and Editing.

Funding: The research in this paper has been supported by the National Science Centre (NCN, Poland), under Grant no. 2020/39/D/HS4/02384.

Data Availability Statement: All datasets and materials employed in the analytical and computational processes of this study are obtained from publicly accessible sources. The data supporting the findings of this research will be publicly available after the publication of this article.

Conflicts of Interest: The authors affirm no conflict of interest.

References

1. Acharjya, D. P., & Rathi, R. (2021). An extensive study of statistical, rough, and hybridized rough computing in bankruptcy prediction. *Multimedia Tools and Applications*, 80(28), 35387–35413. <https://doi.org/10.1007/s11042-020-10167-2>.
2. Adisa, J. A., Ojo, S., Owolawi, P. A., Pretorius, A., & Ojo, S. O. (2023). Application of an improved optimization using learning strategies and long short term-memory for bankruptcy prediction. *IAENG International Journal of Computer Science*, 50(2), 512–524.
3. Ágoston, N. (2022). Mesterséges intelligencia és gépi tanulási módszerek a vállalati fizetéseképtelenség becslésére. *Statistikai Szemle*, 100(6), 584–609. <https://doi.org/10.20311/stat2022.6.hu0584>.
4. Ahmed, S., Alshater, M. M., El Ammari, A., & Hammami, H. (2022). Artificial intelligence and machine learning in finance: A bibliometric review. *Research in International Business and Finance*, 61, Article 101646. <https://doi.org/10.1016/j.ribaf.2022.101646>.
5. Ainan, U. H., Por, L. Y., Chen, Y.-L., Yang, J., & Ku, C. S. (2024). Advancing bankruptcy forecasting with hybrid machine learning techniques: Insights from an unbalanced Polish dataset. *IEEE Access*, 12, 9369–9381. <https://doi.org/10.1109/ACCESS.2024.3354173>.
6. Alaka, H. A., Oyedele, L. O., Owolabi, H. A., Kumar, V., Ajayi, S. O., Akinade, O. O., & Bilal, M. (2018). Systematic review of bankruptcy prediction models: Towards a framework for tool selection. *Expert Systems with Applications*, 94, 164–184. <https://doi.org/10.1016/j.eswa.2017.10.040>.
7. Alam, T. M., Shaukat, K., Mushtaq, M., Ali, Y., Khushi, M., Luo, S., & Wahab, A. (2021). Corporate bankruptcy prediction: An approach towards better corporate world. *The Computer Journal*, 64(11), 1731–1746. <https://doi.org/10.1093/comjnl/bxaa056>.
8. Aljawazneh, H., Mora, A. M., García-Sánchez, P., & Castillo-Valdivieso, P. A. (2021). Comparing the performance of deep learning methods to predict companies' financial failure. *IEEE Access*, 9, 97010–97038. <https://doi.org/10.1109/ACCESS.2021.3093461>.
9. Al-Milli, N., Hudaib, A., & Obeid, N. (2021). Population diversity control of genetic algorithm using a novel injection method for bankruptcy prediction problem. *Mathematics*, 9(8), Article 823. <https://doi.org/10.3390/math9080823>.
10. Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance*, 23(4), 589–609. <https://doi.org/10.2307/2978933>.
11. Aly, S., Alfonse, M., Rousdy, M. I., & Salem, A.-B. M. (2022). Developing an intelligent system for predicting bankruptcy. *Journal of Theoretical and Applied Information Technology*, 100(7), 2068–2088.
12. Amirshahi, B., & Lahmiri, S. (2024). Bankruptcy prediction using optimal ensemble models under balanced and imbalanced data. *Expert Systems*, 41(8), 1–25. <https://doi.org/10.1111/exsy.13599>.
13. Antonowicz, P. (2010). Zastosowanie macierzy klasyfikacji przedsiębiorstw do oceny zdolności predykcyjnych 52 modeli Z-score. *Zeszyty Naukowe Politechniki Rzeszowskiej. Zarządzanie i Marketing*, 17(1), 19–28.
14. Appenzeller, D. (2001). Models for corporate failure prediction in Poland. *Argumenta Oeconomica*, 1, 91–108.
15. Appenzeller, D., & Szarzec, K. (2004). Prognozowanie zagrożenia upadłością polskich spółek publicznych. *Rynek Terminowy*, 1, 120–128.
16. Balina, R. (2018). Forecasting bankruptcy risk in the context of credit risk management: A case study on the wholesale food industry in Poland. *International Journal of Economic Sciences*, 7(1), 1–15. <https://doi.org/10.20472/ES.2018.7.1.001>.
17. Balina, R., & Juszczak, S. (2014). Forecasting bankruptcy risk of international commercial road transport companies. *International Journal of Management and Enterprise Development*, 13(1), 1–20. <https://doi.org/10.1504/IJMED.2014.059848>.

18. Bareith, T., Koroseczné, P. R., & Köővér, G. (2014). Felszámolások vizsgálata a Nyugat-dunántúli régióban. *E-conom*, 3(2), 102–124. <https://doi.org/10.17836/EC.2014.2.102>.
19. Beaver, W. H. (1966). Financial ratios as predictors of failure. *Journal of Accounting Research*, 71–111. <https://doi.org/10.2307/2490171>.
20. Bellovary, J. L., Giacomino, D. E., & Akers, M. D. (2007). A review of bankruptcy prediction studies: 1930 to present. *Journal of Financial Education*, 33, 1–42.
21. Bemš, J., Stary, O., Macas, M., Zegklitz, J., & Posík, P. (2015). Innovative default prediction approach. *Expert Systems with Applications*, 42(17–18), 6277–6285. <https://doi.org/10.1016/j.eswa.2015.04.053>.
22. Boďa, M. (2009). Predicting bankruptcy of Slovak enterprises by an artificial neural network. *Forum Statisticum Slovacum*, 6, 3–6.
23. Boďa, M., & Uradníček, V. (2016). The portability of Altman's Z-score model to predicting corporate financial distress of Slovak companies. *Technological and Economic Development of Economy*, 22(4), 532–553. <https://doi.org/10.3846/20294913.2016.1197165>.
24. Bozsik, J. (2011). Decision tree combined with neural networks for financial forecast. *Periodica Polytechnica Electrical Engineering*, 55(3–4), 95–101. <https://doi.org/10.3311/pp.ee.2011-3-4.01>.
25. Čámská, D. (2016). Accuracy of models predicting corporate bankruptcy in a selected industry branch. *Ekonomický časopis*, 64(4), 353–366.
26. Chakraborty, D., & Ranjan, R. (2024). Missing data imputation with granular semantics and AI-driven pipeline for bankruptcy prediction. *arXiv preprint*, arXiv:2404.00013. <https://arxiv.org/abs/2404.00013>.
27. Chrastinová, Z. (1998). *Methods of assessing economic creditworthiness and predicting the financial situation of agricultural enterprises* [Metódy hodnotenia ekonomickej bonity a predikcie finančnej situácie poľnohospodárskych podnikov]. VUEPP.
28. Danišovská, M., & Stachová, M. (2019). Predikcia finančného zdravia vybraných podnikov v Slovenskej republike [Predicting financial health of selected companies in the Slovak Republic]. *Forum Statisticum Slovacum*, 15(1), 10–28.
29. Dasilas, A., & Rigani, A. (2024). Machine learning techniques in bankruptcy prediction: A systematic literature review. *Expert Systems with Applications*, 255, Article124761. <https://doi.org/10.1016/j.eswa.2024.124761>.
30. Dębkowska, K. (2012). Modelowanie upadłości przedsiębiorstw przy wykorzystaniu metod dyskryminacji i regresji. *Prace Naukowe Uniwersytetu Ekonomicznego we Wrocławiu*, 242, 222–230.
31. Dębkowska, K. (2013). Modelowanie upadłości przedsiębiorstw oparte na próbach niezbilansowanych. *Prace Naukowe Uniwersytetu Ekonomicznego we Wrocławiu*, 279, 226–234.
32. Delina, R., & Packová, M. (2013). Validation of predictive bankruptcy models in the conditions of the Slovak Republic [Validácia predikčných bankrotových modelov v podmienkach SR]. *Ekonomie a Management*, 16(3), 101–112.
33. Dervovic, D., Lecue, F., Marchesotti, N., & Magazzeni, D. (2024). Are logistic models really interpretable? *arXiv preprint*, arXiv:2406.13427. <https://arxiv.org/abs/2406.13427>.
34. Durica, M., Frnda, J., & Svabova, L. (2023). Artificial neural network and decision tree-based modelling of non-prosperity of companies. *Equilibrium. Quarterly Journal of Economics and Economic Policy*, 18(4), 1105–1131. <https://doi.org/10.24136/eq.2023.035>.
35. Durica, M., & Mazanec, J. (2022). Modeling the financial distress of Slovak companies using various decision trees. In *Business and Management 2022: 12th International Scientific Conference* (pp. 845–851). <https://doi.org/10.3846/bm.2022.850>.
36. Durica, M., Frnda, J., & Svabova, L. (2019a). Decision tree-based model of business failure prediction for Polish companies. *Oeconomia Copernicana*, 10(3), 453–469. <https://doi.org/10.24136/oc.2019.022>.

37. Durica, M., Valaskova, K., & Janoskova, K. (2019b). Logit business failure prediction in V4 countries. *Engineering Management in Production and Services*, 11(4), 54–64. <https://doi.org/10.2478/emj-2019-0033>.
38. Dvořáček, J., Sousedíková, R., Barták, P., Štěrbá, J., & Novák, K. (2012a). Forecasting companies' future economic development. *Acta Montanistica Slovaca*, 17, 111–118.
39. Dvořáček, J., Sousedíková, R., & Domarácká, L. (2008). Industrial enterprises bankruptcy forecasting. *Metalurgija*, 47(1), 33–36.
40. Dvořáček, J., Sousedíková, R., Repka, M., Domarácká, L., Barták, P., & Bartošíková, M. (2012b). Choosing a method for predicting economic performance of companies. *Metalurgija*, 51(4), 525–528.
41. Dzik-Walczak, A., & Odziemczyk, M. (2021). Modelling cross-sectional tabular data using convolutional neural networks: Prediction of corporate bankruptcy in Poland. *Central European Economic Journal*, 8(55), 352–377. <https://doi.org/10.2478/ceej-2021-0024>.
42. Ékes, S. K., & Koloszár, L. (2014). The efficiency of bankruptcy forecast models in the Hungarian SME sector. *Journal of Competitiveness*, 6(2), 56–73. <https://doi.org/10.7441/joc.2014.02.05>.
43. Elhoseny, M., Metawa, N., & El-Hasnony, I. M. (2022a). Deep learning-based model for financial distress prediction. *Annals of Operations Research*, 345, 1–23. <https://doi.org/10.1007/s10479-022-04766-5>.
44. Elhoseny, M., Metawa, N., & El-Hasnony, I. M. (2022b). A new metaheuristic optimization model for financial crisis prediction: Towards sustainable development. *Sustainable Computing: Informatics and Systems*, 35, Article 100778. <https://doi.org/10.1016/j.suscom.2022.100778>.
45. Felföldi-Szücs, N. (2015). A vevői nemfizetés előrejelzése viselkedési jellemzők segítségével. *Gradus*, 2(2), 1–9. <https://real-j.mtak.hu/16946/2/2015-2.pdf>.
46. Fitzpatrick, P. J. (1932). A comparison of the ratios of successful industrial enterprises with those of failed companies. *Certified Public Accountant*, 66, 727–731.
47. García, V., Marqués, A. I., & Sánchez, J. S. (2019). Exploring the synergetic effects of sample types on the performance of ensembles for credit risk and corporate bankruptcy prediction. *Information Fusion*, 47, 88–101. <https://doi.org/10.1016/j.inffus.2018.07.004>.
48. Gaska, D. (2013). Zastosowanie metody SVM do oceny ryzyka bankructwa i prognozowania upadłości przedsiębiorstw. *Śląski Przegląd Statystyczny*, 17(11), 289–310.
49. Gaska, D. (2015). Prognozowanie bankructwa za pomocą klasyfikatorów rozmytych realizujących ideę maksymalnego marginesu. *Śląski Przegląd Statystyczny*, 19(13), 71–88.
50. Gavliak, R. (2006). Bankruptcy prediction in Slovak companies using linear probability models. *Forum Statisticum Slovacum*, 2(5), 65–69.
51. Gavurová, B., Janke, F., Packová, M., & Pridavok, M. (2017). Analysis of impact of using trend variables on bankruptcy prediction model performance. *Ekonomický časopis*, 65(4), 370–383.
52. Gavurova, B., Jencova, S., Bacik, R., Miskufova, M., & Letkovsky, S. (2022). Artificial intelligence in predicting the bankruptcy of non-financial corporations. *Oeconomia Copernicana*, 13(4), 1215–1251. <https://doi.org/10.24136/oc.2022.035>.
53. Geise, A., Kuczmarska, M., & Pawłowski, J. (2021). Corporate failure prediction of construction companies in Poland: Evidence from LR model. *European Research Studies Journal*, 24(1), 99–116. <https://doi.org/10.35808/ersj/1952>.
54. Gregova, E., Valaskova, K., Adamko, P., Tumpach, M., & Jaros, J. (2020). Predicting financial distress of Slovak enterprises: Comparison of selected traditional and learning algorithms methods. *Sustainability*, 12, Article 3954. <https://doi.org/10.3390/su12103954>.
55. Gruszczynski, M. (2004). Financial distress of companies in Poland. *International Advances in Economic Research*, 10(4), 249–256.
56. Gulka, M. (2016). Bankruptcy prediction model of commercial companies operating in the conditions of the Slovak Republic [Model predikcie úpadku obchodných spoločností podnikajúcich v podmienkach SR]. *Forum Statisticum Slovacum*, 12(1), 16–22.

57. Gurčík, L. (2002). G-index – The financial situation prognosis method of agricultural enterprises. *Agricultural Economics (Zemědělská ekonomika)*, 48(8), 373–378. <https://doi.org/10.17221/5338-AGRICECON>.
58. Hajdu, O., & Virág, M. (2001). A Hungarian model for predicting financial bankruptcy. *Society and Economy*, 23(1–2), 28–46. <https://www.jstor.org/stable/41468499>.
59. Hamrol, M., Czajka, B., & Piechocki, M. (2004). Upadłość przedsiębiorstwa – model analizy dyskryminacyjnej. *Przegląd Organizacji*, 6, 35–39.
60. Harumová, A., & Janisová, M. (2014). Rating Slovak enterprises by scoring functions. *Ekonomický časopis*, 62(5), 522–539.
61. Hiadlovský, V., & Král, P. (2005). Využitie diskriminačnej analýzy na predikovanie finančnej situácie podnikov v SR. *Forum Statisticum Slovaca*, 1(1), 44–49.
62. Hiadlovský, V., & Král, P. (2006). Možnosti predikovania finančnej situácie podnikov v SR s využitím SPSS. *Forum Statisticum Slovaca*, 2(4), 90–95.
63. Hilal, A. M., Alsolai, H., Al-Wesabi, F. N., Al-Hagery, M. A., Hamza, M. A., & Al Duhayyim, M. (2022). Artificial intelligence-based optimal functional link neural network for financial data science. *Computers, Materials & Continua*, 70(3), 6289–6304.
64. Hołda, A. (2001). Prognozowanie bankructwa jednostki w warunkach gospodarki polskiej z wykorzystaniem funkcji dyskryminacyjnej ZH. *Rachunkowość*, 5(200), 306–331.
65. Horváth, G. (2021). Vállalatok hitelkockázati modellezése a Magyar Nemzeti Bank felügyeleti stressztesztjében. *Hitelintézeti Szemle*, 20(1), 43–73. <https://doi.org/10.25201/HSZ.20.1.4373>.
66. Horváthová, J., & Mokrišová, M. (2018). Risk of bankruptcy, its determinants and models. *Risks*, 6(4), Article 117. <https://doi.org/10.3390/risks6040117>.
67. Horváthová, J., & Mokrišová, M. (2020). Comparison of the results of a data envelopment analysis model and logit model in assessing business financial health. *Information*, 11(3), Article 160. <https://doi.org/10.3390/info11030160>.
68. Horváthová, J., Mokrišová, M., & Bača, M. (2023). Bankruptcy prediction for sustainability of businesses: The application of graph theoretical modeling. *Mathematics*, 11(24), Article 4966. <https://doi.org/10.3390/math11244966>.
69. Horváthová, J., Mokrišová, M., & Petruška, I. (2021). Selected methods of predicting financial health of companies: Neural networks versus discriminant analysis. *Information*, 12(12), Article 505. <https://doi.org/10.3390/info12120505>.
70. Hurtošová, J. (2009). *Construction of a rating model, a tool for assessing the creditworthiness of a company* [Konstrukcia ratingového modelu, nástroja hodnotenia úverovej spôsobilosti podniku] [Dissertation thesis]. University of Economics in Bratislava.
71. Inzelt, G., Szappanos, G., & Ármái, Z. (2016). Felügyelet robustus kockázati monitoring alkalmazásával – Ciklusfüggetlen magyar vállalati minősítő rendszer. *Hitelintézeti Szemle*, 15(3), 51–78. <https://hitelintezetiszemle.mnb.hu/letoltes/inzelt-gyorgy-szappanos-gabor-armai-zsolt.pdf>.
72. Islam, M. T., & Mustafa, H. A. (2023). Multi-layer hybrid (MLH) balancing technique: A combined approach to remove data imbalance. *Data & Knowledge Engineering*, 143, Article 102105. <https://doi.org/10.1016/j.datak.2022.102105>.
73. Iwanowicz, T. (2018). Empiryczna weryfikacja hipotezy o przenoszalności modelu Altmana na warunki polskiej gospodarki oraz uniwersalności sektorowej modeli. *Zeszyty Teoretyczne Rachunkowości*, 96, 63–80. <https://doi.org/10.5604/01.3001.0011.6170>.
74. Jaki, A., & Ćwięk, W. (2020). Bankruptcy prediction models based on value measures. *Journal of Risk and Financial Management*, 14(1), Article 6. <https://doi.org/10.3390/jrfm14010006>.
75. Jakubík, P., & Teplý, P. (2011). The JT index as an indicator of financial stability of the corporate sector. *Prague Economic Papers*, 20(2), 157–176.

76. Jenčová, S., Štefko, R., & Vašaničová, P. (2020). Scoring model of the financial health of the electrical engineering industry's non-financial corporations. *Energies*, 13(17), Article 4364. <https://doi.org/10.3390/en13174364>.
77. Jin, Y., Zhang, W., Wu, X., Liu, Y., & Hu, Z. (2021). A novel multi-stage ensemble model with a hybrid genetic algorithm for credit scoring on imbalanced data. *IEEE Access*, 9, 143593–143607. <https://doi.org/10.1109/ACCESS.2021.3120086>.
78. Juszczak, S., & Balina, R. (2014). Prognozowanie zagrożenia bankructwem przedsiębiorstw w wybranych branżach. *Ekonomista*, 1, 67–95.
79. Kalouda, F., & Vaníček, R. (2013). Alternativní bankrotní modely – první výsledky. In *Evropské finanční systémy: Conference Proceedings* (pp. 143–148).
80. Kanász, R., Gnip, P., Zoričák, M., & Drotár, P. (2023). Bankruptcy prediction using ensemble of autoencoders optimized by genetic algorithm. *PeerJ Computer Science*, 9, Article e1257. <https://doi.org/10.7717/peerj-cs.1257>.
81. Karas, M., & Režňáková, M. (2014). A parametric or nonparametric approach for creating a new bankruptcy prediction model: The evidence from the Czech Republic. *International Journal of Mathematical Models and Methods in Applied Sciences*, 8(1), 214–223.
82. Karas, M., & Režňáková, M. (2017). Predicting the bankruptcy of construction companies: A CART-based model. *Engineering Economics*, 28(2), 145–154. <https://doi.org/10.5755/j01.ee.28.2.16353>.
83. Karas, M., & Režňáková, M. (2020). Cash flow indicators in the prediction of financial distress. *Engineering Economics*, 31(5), 525–535. <https://doi.org/10.5755/j01.ee.31.5.25202>.
84. Karas, M., & Režňáková, M. (2013). Bankruptcy prediction model of industrial enterprises in the Czech Republic. *International Journal of Mathematical Models and Methods in Applied Sciences*, 7(5), 519–531.
85. Karas, M., & Režňáková, M. (2016). An analysis of the robustness of bankruptcy prediction models: Industrial concerns in the Czech Republic in the years 1999–2013. In *Vision 2020: Sustainable Growth, Economic Development, and Global Competitiveness*.
86. Karas, M., & Režňáková, M. (2018). Building a bankruptcy prediction model: Could information about past development increase model accuracy? [Budowanie modelu prognozowania upadłościowego: Czy informacje dotyczące dotychczasowego rozwoju mogą zwiększyć dokładność modelu?]. *Polish Journal of Management Studies*, 17(1), 116–130. <https://doi.org/10.17512/pjms.2018.17.1.10>.
87. Karas, M., & Srbová, P. (2019). Predicting bankruptcy in construction business: Traditional model validation and formulation of a new model. *Journal of International Studies*, 12(1), 192–207.
88. Kisielińska, J. (2016). The effectiveness of corporate bankruptcy models. *Economic and Regional Studies*, 9(1), 5–17.
89. Klietnik, T., Misankova, M., Valaskova, K., & Svabova, L. (2018). Bankruptcy prevention: New effort to reflect on legal and social changes. *Science and Engineering Ethics*, 24(2), 791–803. <https://doi.org/10.1007/s11948-017-9912-4>.
90. Klietnik, T., Vrbka, J., & Rowland, Z. (2018). Bankruptcy prediction in Visegrad Group countries using multiple discriminant analysis. *Equilibrium. Quarterly Journal of Economics and Economic Policy*, 13(3), 569–593. <https://doi.org/10.24136/eq.2018.028>.
91. Kohonen, T. (1997). Exploration of very large databases by self-organizing maps. In *Proceedings of the International Conference on Neural Networks (ICNN'97)* (Vol. 1, pp. PL1–PL6).
92. Kokczyński, B. (2023). Przewidywanie upadłości polskich przedsiębiorstw – zastosowanie analizy dyskryminacyjnej. Wyniki badań pilotażowych. *Współczesna Gospodarka*, 17(2), 81–94. <https://doi.org/10.26881/wg.2023.2.06>.

93. Korol, T. (2013). Early warning models against bankruptcy risk for Central European and Latin American enterprises. *Economic Modelling*, 31, 22–30. <https://doi.org/10.1016/j.econmod.2012.11.017>.
94. Korol, T. (2010b). Prognozowanie upadłości firm przy wykorzystaniu miękkich technik obliczeniowych. *Financial Internet Quarterly*, 6, 1–15.
95. Korol, T. (2010a). Skuteczne metody prognozowania upadłości firm. *Przegląd Organizacji*, 6, 15–18.
96. Kovacova, M., & Klietnik, T. (2017). Logit and probit application for the prediction of bankruptcy in Slovak companies. *Equilibrium. Quarterly Journal of Economics and Economic Policy*, 12(4), 775–791. <https://doi.org/10.24136/eq.v12i4.40>.
97. Kovacova, M., Klietnik, T., Kubala, P., Valakova, K., Radišić, M., & Borocki, J. (2018). Bankruptcy models: Verifying their validity as a predictor of corporate failure. *Polish Journal of Management Studies*, 18(1), 167–179. <https://doi.org/10.17512/pjms.2018.18.1.13>.
98. Kovacova, M., Klietnik, T., Valasková, K., Durana, P., & Juhaszova, Z. (2019). Systematic review of variables applied in bankruptcy prediction models of Visegrad Group countries. *Oeconomia Copernicana*, 10(4), 743–772. <https://doi.org/10.24136/oc.2019.034>.
99. Král, P., Hladlovský, V., & Gavliak, R. (2007). Použitie faktorovej analýzy pri predikcii finančnej situácie podnikov v SR s využitím SPSS. *Forum Statisticum Slovaca*, 3(4), 74–80.
100. Kral, P., Svabova, L., & Durica, M. (2018). Overview of selected bankruptcy prediction models applied in V4 countries. *Balkans Journal of Emerging Trends in Social Sciences*, 1, 70–80.
101. Kristóf, T. (2008). A csődelőrejelzés és a nemfizetési valószínűség számításának módszertani kérdéseiről. *Közgazdasági Szemle*, 55(5), 441–461. <https://epa.oszk.hu/00000/00017/00148/pdf/04-mh-kristof.pdf>.
102. Kristóf, T. (2018). A case-based reasoning alkalmazása a hazai mikrovállalkozások csődelőrejelzésére. *Statisztikai Szemle*, 96(11–12), 1109–1128. <https://doi.org/10.20311/stat2018.11-12.hu1109>.
103. Kristóf, T., & Virág, M. (2012). Data reduction and univariate splitting—Do they together provide better corporate bankruptcy prediction? *Acta Oeconomica*, 62(2), 205–228. <https://doi.org/10.1556/aoecon.62.2012.2.4>.
104. Kristóf, T., & Virág, M. (2020). A comprehensive review of corporate bankruptcy prediction in Hungary. *Journal of Risk and Financial Management*, 13(2), Article 35. <https://doi.org/10.3390/jrfm13020035>.
105. Kruskal, W. H., & Wallis, W. A. (1952). Use of ranks in one-criterion variance analysis. *Journal of the American Statistical Association*, 47(260), 583–621.
106. Kuběnka, M., Honková, I., Sejkora, F., & Mlázovský, M. (2024). The actual predictive power of bankruptcy models in terms of time use. *New Trends in Contemporary Economics, Business and Management*, 438–443. <https://doi.org/10.3846/bm.2024.1302>.
107. Kuběnka, M., & Myšková, R. (2019). Obvious and hidden features of corporate default in bankruptcy models. *Journal of Business Economics and Management*, 20(2), 368–383. <https://doi.org/10.3846/jbem.2019.9612>.
108. Kuběnka, M., Myšková, R., Novotný, J., & Jedlička, V. (2018). The role of apparent signs of financial distress in test samples and verification samples of bankrupt models. In *Proceedings of the 15th International Scientific Conference on European Financial Systems 2018* (pp. 341–347).
109. Kumar, K., Dhanasekaran, S., Punithavathi, I., Duraipandy, P., Dutta, A. K., Pustokhina, I. V., & Pustokhin, D. A. (2022). Bird swarm algorithm with fuzzy min–max neural network for financial crisis prediction. *Computers, Materials & Continua*, 73(1), 1541–1555. <https://doi.org/10.32604/cmc.2022.028338>.
110. Kumar, P. R., & Ravi, V. (2007). Bankruptcy prediction in banks and firms via statistical and intelligent techniques: A review. *European Journal of Operational Research*, 180(1), 1–28. <https://doi.org/10.1016/j.ejor.2006.08.043>.

111. Lahmiri, S., Bekiros, S., Giakoumelou, A., & Bezzina, F. (2020). Performance assessment of ensemble learning systems in financial data classification. *Intelligent Systems in Accounting, Finance and Management*, 27(1), 3–9. <https://doi.org/10.1002/isaf.1460>.
112. Machek, O., Smrčka, L., & Strouhal, J. (2015). How to predict potential default of cultural organizations. In *7th International Scientific Conference: Finance and Performance of Firms in Science, Education and Practice* (p. 893-902).
113. Mączyńska, E. (1994). Ocena kondycji przedsiębiorstwa: Uproszczone metody. *Życie Gospodarcze*, 38, 42–45.
114. Mączyńska, E., & Zawadzki, M. (2006). Dyskryminacyjne modele predykcji upadłości przedsiębiorstw. *Ekonomista*, 2, 205–235.
115. Marso, S., & El Merouani, M. (2020). Bankruptcy prediction using hybrid neural networks with artificial bee colony. *Engineering Letters*, 28(4), 1–10.
116. Márton, A., Fiáth, A., & Kristóf, T. (2023). Állami energiavállalatok pénzügyi teljesítménye Magyarországon a koronavírus-járvány előtt és alatt. *Közgazdasági Szemle*, 70(10), 1057–1076. <https://doi.org/10.18414/KSZ.2023.10.1057>.
117. Mazanec, J., & Bartošová, V. (2021). Prediction model as sustainability tool for assessing financial status of non-profit organizations in the Slovak Republic. *Sustainability*, 13(17), Article 9721. <https://doi.org/10.3390/su13179721>.
118. Mazanec, J., Bartošová, V., & Bohm, P. (2022). Logit model for estimating non-profit organizations' financial status as a part of non-profit financial management. *Mathematics*, 10(13), Article 2162. <https://doi.org/10.3390/math10132162>.
119. Messier, W. F., Jr., & Hansen, J. V. (1988). Inducing rules for expert system development: An example using default and bankruptcy data. *Management Science*, 34(12), 1403–1415.
120. Mihalovič, M. (2016). Performance comparison of multiple discriminant analysis and logit models in bankruptcy prediction. *Economics & Sociology*, 9(4), 101–118. <https://doi.org/10.14254/2071-789X.2016/9-4/6>.
121. Mihalovič, M. (2018). Applicability of scoring models in firms' default prediction: The case of Slovakia. *Politická Ekonomie*, 66(6), 689–708. <https://doi.org/10.18267/j.polek.1226>.
122. Mokrišová, M., & Horváthová, J. (2023). Domain knowledge features versus LASSO features in predicting risk of corporate bankruptcy—DEA approach. *Risks*, 11(11), Article 199. <https://doi.org/10.3390/risks11110199>.
123. Muslim, M. A., & Dasril, Y. (2021). Company bankruptcy prediction framework based on the most influential features using XGBoost and stacking ensemble learning. *International Journal of Electrical and Computer Engineering*, 11(6), 5549–5557. <https://doi.org/10.11591/ijece.v11i6.pp5549-5557>.
124. Němec, D., & Pavlík, M. (2016). Predicting insolvency risk of the Czech companies. In *Proceedings of the International Scientific Conference: Quantitative Methods in Economics – Multiple Criteria Decision Making XVIII* (pp. 258–263).
125. Neumaier, I., & Neumaierová, I. (2001). Analysis of the value formation – Application of financial analysis INFA. *Sektorové a Odvětvové Analýzy Aspekt*, 8(5).
126. Neumaier, I., & Neumaierová, I. (2005). Index IN05. In *Evropské finanční systémy: Sborník příspěvků z mezinárodní vědecké konference*.
127. Noga, T., & Adamowicz, K. (2021). Forecasting bankruptcy in the wood manufacturing. *European Journal of Wood and Wood Products*, 79, 735–743. <https://doi.org/10.1007/s00107-020-01620-y>.
128. Nyitrai, T. (2014a). Növelhető-e a csődelőrejelző modellek előrejelző képessége az új klasszifikációs módszerek nélkül? *Közgazdasági Szemle*, 61(5), 566–585. <https://real.mtak.hu/17341/>.

129. Nyitrai, T. (2014b). Validációs eljárások a csődelőrejelző modellek teljesítményének megítélésében. *Statisztikai Szemle*, 92(4), 357–377. https://www.ksh.hu/statszemle_archive/2014/2014_04/2014_04_357.pdf.
130. Nyitrai, T. (2015). Hazai vállalkozások csődjének előrejelzése a csődeseményt megelőző egy, két, illetve három évvel korábbi pénzügyi beszámolók adatai alapján. *Vezetéstudomány*, 46(5), 55–65. <https://doi.org/10.14267/VEZTUD.2015.05.06>.
131. Nyitrai, T. (2017). Stock és flow típusú számviteli adatok alkalmazása a csődelőrejelző modellekben. *Vezetéstudomány*, 48(8–9), 68–77. <https://doi.org/10.14267/VEZTUD.2017.09.07>.
132. Nyitrai, T. (2018). A vállalatok tevékenységi körének és méretének hatása a csődelőrejelző modellekre. *Statisztikai Szemle*, 96(10), 973–1000. <https://doi.org/10.20311/stat2018.10.hu0973>.
133. Nyitrai, T. (2019a). CHAID-alapú felülvizsgált kategorizálás a csődelőrejelzésben. *Statisztikai Szemle*, 97(7), 656–686. <https://doi.org/10.20311/stat2019.7.hu0656>.
134. Nyitrai, T. (2019b). Dynamization of bankruptcy models via indicator variables. *Benchmarking: An International Journal*, 26(1), 317–332. <https://doi.org/10.1108/BIJ-03-2017-0052>.
135. Nyitrai, T., & Virág, M. (2017a). Magyar vállalkozások felszámolásának előrejelzése pénzügyi mutatóik idősorai alapján. *Közgazdasági Szemle*, 64(3), 305–324. <https://doi.org/10.18414/Ksz.2017.3.305>.
136. Nyitrai, T., & Virág, M. (2017b). A pénzügyi mutatók időbeli tendenciájának figyelembevétele logisztikus regresszióra épülő csődelőrejelző modellekben. *Statisztikai Szemle*, 95(1), 5–28. <https://doi.org/10.20311/stat2017.01.hu0005>.
137. Nyitrai, T., & Virág, M. (2019). The effects of handling outliers on the performance of bankruptcy prediction models. *Socio-Economic Planning Sciences*, 67, 34–42. <https://doi.org/10.1016/j.seps.2018.08.004>.
138. Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research*, 18(1), 109–131. <https://doi.org/10.2307/2490395>.
139. Paliński, A. (2018). Metody uczenia maszynowego w prognozowaniu niewypłacalności. *Studia Ekonomiczne*, 358, 173–181.
140. Paliński, A. (2020). Wykrywanie zagrożenia upadłością jako problem klasyfikacji danych niezbalansowanych. *Studia Ekonomiczne*, 395, 6–79.
141. Papík, M., & Papíková, L. (2023). Impacts of crisis on SME bankruptcy prediction models' performance. *Expert Systems with Applications*, 214, Article 119072. <https://doi.org/10.1016/j.eswa.2022.119072>.
142. Pavlicko, M., Durica, M., & Mazanec, J. (2021). Ensemble model of the financial distress prediction in Visegrad Group countries. *Mathematics*, 9(16), 1–26. <https://doi.org/10.3390/math9161886>.
143. Pavlicko, M., & Mazanec, J. (2022). Minimalistic logit model as an effective tool for predicting the risk of financial distress in the Visegrad Group. *Mathematics*, 10(8), 1–22. <https://doi.org/10.3390/math10081302>.
144. Pawełek, B. (2019). Extreme gradient boosting method in the prediction of company bankruptcy. *Statistics in Transition. New Series*, 20(2), 88–101. <https://doi.org/10.21307/stattrans-2019-020>.
145. Pawełek, B., Baryła, M., & Pociecha, J. (2020). Study of the classification accuracy measures for predicting corporate bankruptcy taking into account changes in the economic environment. *Argumenta Oeconomica*, 1(44), 5–17. <https://doi.org/10.15611/aoe.2020.1.01>.
146. Pawełek, B., & Grochowina, D. (2017). Podejście wielomodelowe w prognozowaniu zagrożenia przedsiębiorstw upadłością w Polsce. *Prace Naukowe Uniwersytetu Ekonomicznego we Wrocławiu*, 468, 171–179. <https://doi.org/10.15611/pn.2017.468.17>.
147. Pisula, T. (2012a). The usage of scoring models to evaluate the risk of bankruptcy on the example of companies from the transport sector. *Scientific Journals of Rzeszów University of Technology, Series: Management and Marketing*, 19, 133–151.

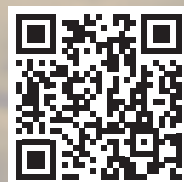
148. Pisula, T. (2012b). Zastosowanie sztucznych sieci neuronowych do prognozowania upadłości przedsiębiorstw. *Prace Naukowe Uniwersytetu Ekonomicznego we Wrocławiu*, 254, 219–234.
149. Pisula, T. (2017). Zastosowanie ensemble klasyfikatorów do oceny ryzyka upadłości przedsiębiorstw na przykładzie firm sektora produkcyjnego działających na Podkarpaciu. *Zarządzanie i Finanse*, 3, 279–293.
150. Pisula, T. (2020). An ensemble classifier-based scoring model for predicting bankruptcy of Polish companies in the Podkarpackie Voivodeship. *Journal of Risk and Financial Management*, 13(2), 1–35. <https://doi.org/10.3390/jrfm13020037>.
151. Pisula, T., Mentel, G., & Brożyna, J. (2013). Predicting bankruptcy of companies from the logistics sector operating in the Podkarpacie region. *Modern Management Review*, 18(20), 113–133.
152. Pisula, T., Mentel, G., & Brożyna, J. (2015). Non-statistical methods of analysing bankruptcy risk. *Folia Oeconomica Stetinensia*, 15(1), 7–21. <https://doi.org/10.1515/fofi-2015-0029>.
153. Pogodzińska, M., & Sojak, S. (1995). Wykorzystanie analizy dyskryminacyjnej w przewidywaniu bankructwa przedsiębiorstw. *Acta Universitatis Nicolai Copernici. Nauki Humanistyczno-Społeczne. Ekonomia*, 25, 53–61.
154. Prusak, B., & Karas, M. (2024). Bankruptcy prediction in Visegrad Group countries. *Polish Journal of Management Studies*, 30(1), 268–288. <https://doi.org/10.17512/pjms.2024.30.1.16>.
155. Prusak, B. (2018). Review of research into enterprise bankruptcy prediction in selected Central and Eastern European countries. *International Journal of Financial Studies*, 6(3), Article 60. <https://doi.org/10.3390/ijfs6030060>.
156. Ptak-Chmielewska, A. (2012). Wykorzystanie modeli przeżycia i analizy dyskryminacyjnej do oceny ryzyka upadłości przedsiębiorstw. *Ekonometria*, 38, 157–172.
157. Ptak-Chmielewska, A. (2021). Bankruptcy prediction of small- and medium-sized enterprises in Poland based on the LDA and SVM methods. *Statistics in Transition. New Series*, 22(1), 179–195. <https://doi.org/10.21307/stattrans-2021-010>.
158. Qian, H., Ma, P., Gao, S., & Song, Y. (2023). Soft reordering one-dimensional convolutional neural network for credit scoring. *Knowledge-Based Systems*, 266, Article 110414. <https://doi.org/10.1016/j.knosys.2023.110414>.
159. Ranjbaran, G., Recupero, D. R., Lombardo, G., & Consoli, S. (2023). Leveraging augmentation techniques for tasks with unbalancedness within the financial domain: A two-level ensemble approach. *EPJ Data Science*, 12(1), 1–31. <https://doi.org/10.1140/epjds/s13688-023-00402-9>.
160. Repetto, M. (2022). Multicriteria interpretability driven deep learning. *Annals of Operations Research*, 346, 1–15. <https://doi.org/10.1007/s10479-022-04692-6>.
161. Režňáková, M., & Karas, M. (2014). Identifying bankruptcy prediction factors in various environments: A contribution to the discussion on the transferability of bankruptcy models. *International Journal of Mathematical Models and Methods in Applied Sciences*, 8(1), 69–74.
162. Rusiecki, K., & Białek-Jaworska, A. (2015). Systemy wczesnego ostrzegania o zagrożeniu upadłością przedsiębiorstw z sektora budowlanego – porównanie analizy dyskryminacyjnej i modelu logitowego. *Ekonomia. Rynek, Gospodarka, Społeczeństwo*, 43, 137–160. <https://doi.org/10.17451/eko/43/2015/126>.
163. Safi, S. A.-D., Castillo, P. A., & Faris, H. (2022). Cost-sensitive metaheuristic optimization-based neural network with ensemble learning for financial distress prediction. *Applied Sciences*, 12(14), 1–32. <https://doi.org/10.3390/app12146918>.
164. Saipriya, N., Harshitha, N., & Bhutada, S. (2022). An intelligent agent system for bankruptcy analysis and prediction. *International Journal of Scientific Research in Science, Engineering and Technology*, 9(3), 364–370. <https://doi.org/10.32628/IJSRSET>.
165. Siegel, S., & Castellan, N. J. (1988). *Nonparametric Statistics for the Behavioural Sciences*. McGraw-Hill.

166. Slaviček, O., & Kuběnka, M. (2016). Bankruptcy prediction models based on logistic regression for companies in the Czech Republic. In *Managing and Modelling of Financial Risks: 8th International Scientific Conference*.
167. Smiti, S., & Soui, M. (2020). Bankruptcy prediction using deep learning approach based on borderline SMOTE. *Information Systems Frontiers*, 22(5), 1067–1083. <https://doi.org/10.1007/s10796-020-10031-6>.
168. Smorada, M., Lukáčková, A., Hajduová, Z., Šrenkel, L., & Havier, J. (2023). Predictive financial analysis as a tool for business management. *TEM Journal*, 12(1), 147–155. <https://doi.org/10.18421/TEM121-20>.
169. Sojak, S., & Konieczka, T. (2004). Ocena bezpieczeństwa finansowego przedsiębiorstw przemysłu cukrowniczego w Polsce przy zastosowaniu procedury dyskryminacyjnej Stawickiego i Sojaka. *Zeszyty Teoretyczne Rachunkowości*, 20(76), 125–143.
170. Sojak, S., & Stawicki, J. (2001). Wykorzystanie metod taksonomicznych do oceny kondycji ekonomicznej przedsiębiorstw. *Zeszyty Teoretyczne Rachunkowości*, 3(59), 45–52.
171. Soui, M., Smiti, S., Mkaouer, M. W., & Ejballi, R. (2020). Bankruptcy prediction using stacked auto-encoders. *Applied Artificial Intelligence*, 34(1), 80–100. <https://doi.org/10.1080/08839514.2019.1691849>.
172. Štefko, R., Horváthová, J., & Mokrišová, M. (2020). Bankruptcy prediction with the use of data envelopment analysis: An empirical study of Slovak businesses. *Journal of Risk and Financial Management*, 13(9), Article 212. <https://doi.org/10.3390/jrfm13090212>.
173. Štefko, R., Horváthová, J., & Mokrišová, M. (2021). The application of graphic methods and DEA in predicting the risk of bankruptcy. *Journal of Risk and Financial Management*, 14(5), Article 220. <https://doi.org/10.3390/jrfm14050220>.
174. Sütő, D. (2018). Észak-alföldi élelmiszer-kiskereskedelmi vállalkozások pénzügyi helyzetének elemzése logitmodell segítségével. *Acta Carolus Robertus*, 8(1), 223–235. <https://doi.org/10.22004/ag.econ.274100>.
175. Svabova, L., Durica, M., & Valaskova, K. (2022). Failure prediction models for Slovak small companies. *European Journal of International Management*, 18(4), Article 617. <https://doi.org/10.1504/EJIM.2022.126164>.
176. Svabova, L., Michalkova, L., Durica, M., & Nica, E. (2020). Business failure prediction for Slovak small and medium-sized companies. *Sustainability*, 12(11), Article 4572. <https://doi.org/10.3390/su12114572>.
177. Szántó, T. K. (2023). Kiugró értékek kezelése logisztikus regresszió alapuló csődelőrejelzési modellek esetén. *Pénzügyi Szemle*, 69(3), 91–106. https://doi.org/10.35551/PFQ_2023_3_5.
178. Szenes, M., & Dabi, Z. (2020). Vállalatok nemteljesítési valószínűségének becslése: Egy lehetséges felügyeleti benchmark-modell. *Hitelintézeti Szemle*, 19(3), 52–77. <https://doi.org/10.25201/HSZ.19.3.5277>.
179. Tarczyński, W. (1996). Analiza dyskryminacyjna na giełdzie papierów wartościowych. *Przegląd Statystyczny*, 43(1–2), 49–66.
180. Tarczyński, W. (1998). Analiza dyskryminacyjna jako narzędzie oceny spółek notowanych na giełdzie papierów wartościowych. *Zeszyty Naukowe Uniwersytetu Szczecińskiego. Prace Katedry Ekonometrii i Statystyki*, 5, 129–151.
181. Tomczak, S. K. (2018). Verification of the effectiveness of re-estimated discriminant models on the example of the food manufacturing sector. *Zarządzanie i Finanse*, 16(4), 193–205.
182. Tomczak, S. K. (2020). Multi-class models for assessing the financial condition of manufacturing enterprises. *Contemporary Economics*, 14(2), 219–235. <https://doi.org/10.5709/ce.1897-9254.401>.
183. Tomczak, S. K. (2021). Ratio selection between six sectors in the Visegrad Group using parametric and non-parametric ANOVA. *Energies*, 14, Article 7120. <https://doi.org/10.3390/en14217120>.

184. Tomczak, S. K. (2023). General bankruptcy prediction models for the Visegrad Group: The stability over time. *Operations Research and Decisions*, 33(4), 171–187. <https://doi.org/10.37190/ord230410>.
185. Tomczak, S. K., & Radosiński, E. (2017). The effectiveness of discriminant models based on the example of the manufacturing sector. *Operations Research and Decisions*, 27(3), 81–97. <https://doi.org/10.5277/ord170306>.
186. Tsai, C.-F. (2020). Two-stage hybrid learning techniques for bankruptcy prediction. *Statistical Analysis and Data Mining: The ASA Data Science Journal*, 13(6), 565–572. <https://doi.org/10.1002/sam.11482>.
187. Uthayakumar, J., Metawa, N., Shankar, K., & Lakshmanaprabu, S. K. (2020). Financial crisis prediction model using ant colony optimization. *International Journal of Information Management*, 50, 538–556. <https://doi.org/10.1016/j.ijinfomgt.2018.12.001>.
188. Vaiyapuri, T., Priyadarshini, K., Hemlathadhevi, A., Dhamodaran, M., Dutta, A. K., Pustokhina, I. V., & Pustokhin, D. A. (2022). Intelligent feature selection with deep learning-based financial risk assessment model. *Computers, Materials & Continua*, 72(2), 2429–2444. <https://doi.org/10.32604/cmc.2022.026204>.
189. Valaskova, K., Durana, P., Adamko, P., & Jaros, J. (2020). Financial compass for Slovak enterprises: Modeling economic stability of agricultural entities. *Journal of Risk and Financial Management*, 13(5), Article 92. <https://doi.org/10.3390/jrfm13050092>.
190. Valaskova, K., Gajdosikova, D., & Belas, J. (2023). Bankruptcy prediction in the post-pandemic period: A case study of Visegrad Group countries. *Oeconomia Copernicana*, 14(1), 253–293. <https://doi.org/10.24136/oc.2023.007>.
191. Valaskova, K., Klietk, T., & Kovacova, M. (2018). Management of financial risks in Slovak enterprises using regression analysis. *Oeconomia Copernicana*, 9(1), 105–121. <https://doi.org/10.24136/oc.2018.006>.
192. Valecký, J., & Slivková, E. (2012). Mikroekonomický scoringový model úpadku českých podniků. *Ekonomická revue*, 15(1), 15–26. <https://doi.org/10.7327/cerei.2012.03.02>.
193. Van der Schraelen, L., Stouthuysen, K., Broucke, S. V., & Verdonck, T. (2023). Regularization oversampling for classification tasks: To exploit what you do not know. *Information Sciences*, 635, 169–194. <https://doi.org/10.1016/j.ins.2023.03.146>.
194. Varetto, F. (1998). Genetic algorithms applications in the analysis of insolvency risk. *Journal of Banking & Finance*, 22(10–11), 1421–1439. [https://doi.org/10.1016/S0378-4266\(98\)00059-4](https://doi.org/10.1016/S0378-4266(98)00059-4).
195. Vavrina, J., Hampel, D., & Janova, J. (2013). New approaches for the financial distress classification in agribusiness. *Acta Universitatis Agriculturae et Silviculturae Mendelianae Brunensis*, 61(4), 1177–1182. <https://doi.org/10.11118/actaun201361041177>.
196. Virág, M., & Kristóf, T. (2005). Neural networks in bankruptcy prediction: A comparative study on the basis of the first Hungarian bankruptcy model. *Acta Oeconomica*, 55(4), 403–426. <https://doi.org/10.1556/AOecon.55.2005.4.2>.
197. Virág, M., & Kristóf, T. (2006). Iparági rátákon alapuló csődelőrejelzés sokváltozós statisztikai módszerekkel. *Vezetéstudomány*, 37(1), 25–35. <https://doi.org/10.14267/VEZTUD.2006.01.04>.
198. Virág, M., & Kristóf, T. (2009). A többdimenziós skálázás a csődmodellezésben. *Vezetéstudomány*, 40(1), 50–58. <https://doi.org/10.14267/VEZTUD.2009.01.05>.
199. Virág, M., & Nyitrai, T. (2013). Application of support vector machines on the basis of the first Hungarian bankruptcy model. *Society and Economy*, 35(2), 227–248. <https://doi.org/10.1556/SocEc.35.2013.2.6>.
200. Virág, M., & Nyitrai, T. (2014a). Is there a trade-off between the predictive power and the interpretability of bankruptcy models? The case of the first Hungarian bankruptcy prediction model. *Acta Oeconomica*, 64(4), 419–440. <https://doi.org/10.1556/AOecon.64.2014.4.2>.
201. Virág, M., & Nyitrai, T. (2014b). Metamódszerek alkalmazása a csődelőrejelzésben. *Hitelintézet Szemle*, 13(4), 180–195. <https://hitelintezetiszemle.mnb.hu/letoltes/hsz-2014-4-1.pdf>.

202. Vochozka, M. (2017). Formation of complex company evaluation method through neural networks based on the example of construction companies collection. In *Innovation Management, Entrepreneurship and Sustainability (IMES 2018)* (pp. 1119–1128). Vysoká škola ekonomická v Praze.
203. Vochozka, M., & Rowland, Z. (2015). Prediction of the future development of construction companies by means of artificial neural networks on the basis of data from the Czech Republic. *Mathematical Modeling in Economics*, 3, 62–76.
204. Vochozka, M., Rowland, Z., & Vrbka, J. (2016). Evaluation of solvency of potential customers of a company. *Mathematical Modeling in Economics*, 1, 5–18.
205. Vochozka, M., Straková, J., & Váchal, J. (2015). Model to predict survival of transportation and shipping companies [Model za predvianje opstanka prijevoznih i brodarskih kompanija]. *Naše More*, 62, 109–113. <https://doi.org/10.17818/NM/2015/SI4>.
206. Waszkowski, A. (2013). Wielomianowy uporządkowany model logitowy w prognozowaniu zagrożenia finansowego przedsiębiorstw. *Problemy Rolnictwa Światowego*, 13(28), 156–163.
207. Wędzki, D. (2012). The sequence of cash flow in bankruptcy prediction: Evidence from Poland. *Zeszyty Teoretyczne Rachunkowości*, 68, 161–179.
208. Wędzki, D. (2005b). A bankruptcy LR model for the Polish economy. *Argumenta Oeconomica Cracoviensia*, 3, 49–70.
209. Wędzki, D. (2005a). Wielowymiarowa analiza bankructwa na przykładzie budownictwa. *Badania Operacyjne i Decyzje*, 2, 59–81.
210. Wędzki, D. (2005c). Zastosowanie logitowego modelu upadłości przedsiębiorstw. *Ekonomista*, 5, 691–705.
211. Wei, S., Yang, D., Zhang, W., & Zhang, S. (2019). A novel noise-adapted two-layer ensemble model for credit scoring based on backflow learning. *IEEE Access*, 7, 99217–99230. <https://doi.org/10.1109/ACCESS.2019.2930332>.
212. Weissová, I. (2017). Applicability of selected predictive models in the Slovak companies. In D. Procházka (Ed.), *New trends in finance and accounting* (pp. 699–708). Springer International Publishing. https://doi.org/10.1007/978-3-319-49559-0_64.
213. Weissova, I., Siekelova, A., & Kramarova, K. (2016). Modeling of company's default probability in relation to its credit risk. *Global Journal of Business, Economics and Management: Current Issues*, 6(2), 130–137. <https://doi.org/10.18844/gjbem.v6i2.1378>.
214. Wierzba, D. (2000). Wczesne wykrywanie przedsiębiorstw zagrożonych upadłością na podstawie analizy wskaźników finansowych – teoria i badania empiryczne. *Zeszyty Naukowe Wyższej Szkoły Ekonomiczno-Informatycznej w Warszawie*, 9, 79–105.
215. Wójcicka, A. (2017). Neural networks vs discriminant analysis in the assessment of default. *Annales Universitatis Mariae Curie-Skłodowska, Sectio H Oeconomia*, 51(5), 339–349. <https://doi.org/10.17951/h.2017.51.5.339>.
216. Wojnar, J. (2015). Analiza porównawcza modelowania logitowego i liniowej funkcji dyskryminacyjnej w ocenie ryzyka upadłości spółek giełdowych. *Metody Ilościowe w Badaniach Ekonomicznych*, 16(4), 201–210.
217. Wu, X., Yang, D., Zhang, W., & Zhang, S. (2019). A hybrid ensemble model for corporate bankruptcy prediction based on feature engineering method. *International Journal of Information and Communication Sciences*, 4(3), 52–58. <https://doi.org/10.11648/j.ijics.20190403.12>.
218. Yang, D., Xiao, B., Cao, M., & Shen, H. (2024). A new hybrid credit scoring ensemble model with feature enhancement and soft voting weight optimization. *Expert Systems with Applications*, 238, Article 122101. <https://doi.org/10.1016/j.eswa.2023.122101>.
219. Yang, D., Zhang, W., Wu, X., Ablanedo-Rosas, J. H., Yang, L., & Yu, W. (2021). A novel multi-stage ensemble model with fuzzy clustering and optimized classifier composition for corporate

- bankruptcy prediction. *Journal of Intelligent & Fuzzy Systems*, 40(3), 4169–4185. <https://doi.org/10.3233/JIFS-200741>.
220. Yotsawat, W., Wattuya, P., & Srivihok, A. (2021). Improved credit scoring model using XGBoost with Bayesian hyper-parameter optimization. *International Journal of Electrical and Computer Engineering*, 11(6), 5477–5487. <https://doi.org/10.11591/ijece.v11i6.pp5477-5487>.
221. Zalai, K. (2000). Osobitosti prognózovania finančného vývoja slovenských podnikov. *BIATEC*, 8(38), 12–14.
222. Zanka, M. (2020). A comparison of variables selection methods and their sequential application: A case study of the bankruptcy of Polish companies. *Folia Oeconomica Stetinensia*, 20(1), 531–543. <https://doi.org/10.2478/fofi-2020-0031>.
223. Zawadzki, J., & Babis, H. (1998). Zastosowania analizy dyskryminacyjnej do oceny kondycji finansowej przedsiębiorstw. *Zeszyty Naukowe Uniwersytetu Szczecińskiego. Prace Katedry Ekonometrii i Statystyki*, 5, 177–185.
224. Zelenkov, Y., & Volodarskiy, N. (2021). Bankruptcy prediction on the base of unbalanced data using multi-objective selection of classifiers. *Expert Systems with Applications*, 185, 115559. <https://doi.org/10.1016/j.eswa.2021.115559>.
225. Zhang, W., Yang, D., Zhang, S., Ablanedo-Rosas, J. H., Wu, X., & Lou, Y. (2021). A novel multi-stage ensemble model with enhanced outlier adaptation for credit scoring. *Expert Systems with Applications*, 165, Article 113872. <https://doi.org/10.1016/j.eswa.2020.113872>.
226. Zięba, M., Tomczak, S. K., & Tomczak, J. M. (2016). Ensemble boosted trees with synthetic features generation in application to bankruptcy prediction. *Expert Systems with Applications*, 58, 93–101. <https://doi.org/10.1016/j.eswa.2016>.



WSB University

Dąbrowa Górnicza, Cieplaka 1c, tel.: +48322959359, e-mail: wydawnictwo@wsb.edu.pl