
Quantification of relationships between artificial intelligence adoption in entrepreneurial enterprises and green innovation in European Union countries

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Beata Gavurova

*Faculty of Management and Economics,
Center for Applied Economic Research, Tomas Bata University in Zlin, Zlín, Czechia*

Samuel Ribeiro-Navarrete

*Lithuanian Centre for Social Sciences, Vilnius University, Kaunas, Lithuania and
VIZJA University, Warsaw, Poland*

Martin Rigelsky

*Faculty of Management and Business, Prešovská univerzita v Prešove,
Prešov, Slovakia, and*

Andrea Mara Pimenta-Alonso

Department of Economics and Finances, ESIC University, Pozuelo de Alarcón, Spain

Abstract

Purpose – The goal of the study was to quantify the relationships between AI adaption in enterprises regarding their size and the green innovation outcomes represented by the eco-innovation index in the European Union countries. Achieving this goal was supported by seven research questions based on the outcomes of available research studies and the defined research gap.

Design/methodology/approach – The data for the year 2021 was examined for all the EU countries ($n = 27$). The seven areas of AI use were processed in enterprises classified by size into small, medium and large entities. The Eco-innovation Index was applied as part of eco-innovation. Regression and cluster analysis (CA) were used for analytical processes. The results of the regression models revealed the existence of significant relationships, but these relationships were closest, especially in large enterprises.

Findings – Medium-sized enterprises demonstrated a lower level of interconnection between AI and eco-innovation outputs; the least significant interconnections were found in small enterprises. The results of the CA pointed to the position of the EU countries. It was found that Bulgaria, Poland, Hungary, Romania and Slovakia were among the countries with the lowest outcomes in the field of AI use in the business sector and eco-innovation, and the Nordic countries, such as Denmark, Finland and Sweden, were among the countries with the most positive outcomes.

Practical implications – The study outcomes will be significant for policymakers dealing with the digital transformation processes, for regulators and creators of strategic development plans at the regional and national levels. They will also support the creation of international databases for the preparation of comparative analyses, the implementation of complementary qualitative research and experiments revealing the barriers to the adoption of digital transformation technologies and their impact on the eco-innovation outputs of enterprises.

JEL Classification — M10, M20, O30, O33

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Originality/value – The study outcomes will be significant for policymakers dealing with the digital transformation processes, for regulators and creators of strategic development plans at the regional and national levels.

Keywords Artificial intelligence, Digital transformation, Eco-innovation, Enterprise size, European Union, Regression analysis, Cluster analysis

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1. Introduction

In the recent period, many enterprises across various sectors have adopted artificial intelligence (AI) systems and technologies to support their management and innovation processes, supply chains, marketing, sales and various other business processes. A significant share of automation in production activities improves efficiency and the decision-making process, supported by increasingly accurate, timely and reliable forecasts. Some studies draw attention to the social value of AI, which is the combined value obtained when a firm's stakeholders adopt AI (Leszkiewicz *et al.*, 2022; Aizenberg and Van Den Hoven, 2020). The social value of AI is expected to increase, as the primary barriers for its adoption will gradually decrease, including the cost of the technologies (Häußermann and Lütge, 2022). Hence, it is important to examine the benefits of using AI by various entrepreneurship actors, business partners and supplier–customer relationship partners. The published Coordinated Plan on Artificial Intelligence 2021 published by the European Commission (EC, 2021) shows that the European Union (EU) aims to accelerate and align political priorities and investments in AI with the aim of achieving global leadership in Europe via adopting the latest technologies, applying the benefits and supporting development aimed at human and achieving sustainable, safe, inclusive and trustworthy AI. Despite the growing importance of AI technologies and the digital transformation processes, including transforming an economy to a circular economy (CE), studies that focus on conceptually exploring the development of relationships between AI, CE and innovation are missing. As reported by Mariani *et al.* (2023), there is a single review of the literature by Haefner *et al.* (2021) that examines the role of AI in supporting innovation. Mariani *et al.* (2023) identified various research gaps in relation to the economic, technological and social forces that motivate enterprises to spur innovation. These authors also identified the research gaps in AI adoption, focusing on the economic, organisational and innovation outcomes. Our study investigated another dimension of this research gap, that is, research on the relationship between AI adoption in various business processes and eco-innovation outcomes. However, it is not possible to achieve the goals of improved performance, efficiency and sustainability through AI technologies without considering the eco-innovation aspects that lead to eco-innovation outcomes.

2. Literature review

Research studies investigating the relationship between AI and technological eco-innovation in the national and international environments are limited. Primarily, most of the research examines the relationship between AI, economic growth and productivity (Lu, 2021; Vijayakumar, 2021), while the concept of green technologies is missing in these studies (Zhao *et al.*, 2022). Notably, AI can play a pivotal role in the innovation processes of enterprises: investigation of problems, analysis of innovations, selection of solutions and the evaluation of outcomes. AI derives considerable value from big data, enabling innovation teams to perform comprehensive analysis and create innovation scenarios (Kakatkar *et al.*, 2020). These are important for the decision-making process, wherein AI technologies can also play a key role. Notably, AI can redesign industries, as evident from the rising innovation observed in business models. Aspects such as organisational design, culture and values play a significant role in the development of innovative business models (Lee *et al.*, 2019). The causal relationships with aspects of process management and efficiency, influenced by AI technologies, have not been

sufficiently explored. Green technology innovation is a technological innovation behaviour that follows the laws of the ecological economy and ecological principles, saves energy and resources and prevents or reduces environmental pollution.

2.1 Interconnectedness of AI technologies and green technology innovation

Johl and Toha (2021) reason that it is important to investigate not only reactive eco-innovation approaches but also proactive ones. The proactive approaches directly increase the financial performance of enterprises and ensure sustainable development. Larbi-Siaw *et al.* (2022) investigated the dimensions of the sustainable performance of enterprises. In many enterprises, a double transition (digital and green) takes place simultaneously, which allows combining investments in digital technologies and eco-innovations in production processes and models (Montesor and Vezzani, 2023). Digital investments and AI are expected to influence eco-innovation in enterprises.

According to Montesor and Vezzani (2023), enterprise size has a significant impact on the interconnection of eco-innovation with investments in digital technologies. Moreover, López Pérez *et al.* (2023) confirm that enterprise size and the environment in which it was established determine eco-innovation development with an impact on financial performance. Few studies discuss the procedure for successful eco-innovation development across various sectors and in enterprises of varied sizes. Cherifi *et al.* (2019) propose a methodological approach to achieve the eco-innovation goals for both small and medium-sized enterprises (SMEs) in the development of their products through the implementation of the TRIZ (Teorija Reshenija Izobretateliskih Zadatch) inventive principles. According to Calafat-Marzal *et al.* (2023), sectoral differentiation has a significant impact on the rate, speed and form of digitalisation implementation. Enterprises with a higher level of digitalisation processes proactively introduce products and radical innovations and are eco-innovative and focused on sustainability (Haller *et al.*, 2023). The digitalisation of a sector is influenced by the depth of technology implementation (big data, Internet of Things [IoT], AI).

While investigating the integration of AI digitalisation across various industrial sectors, it is necessary to also examine the digital culture, AI applications, digital marketing and augmented reality technologies for the emergence of innovations (Ho, 2023) and proactive employee behaviour (Weigt-Rohrbeck and Linneberg, 2019). Enterprise technological resources, which influence the innovation of the ecological processes and services, play a significant role. Regulators and policymakers can stimulate innovative development and support eco-innovation and sustainability (Doran and Ryan, 2012).

Based on these findings, we propose the following research hypothesis 1.

- H1. The relationship between the number of enterprises using AI for marketing or sales and eco-innovation outcomes is significant in the EU countries.

Studies investigating the impact of AI on eco-innovation outcomes perceive the digitalisation process of enterprises as part of the digitalised environment that enterprises originate and develop (Peiró-Signes and Segarra-Oña, 2018; Scarpellini *et al.*, 2020a, b). This makes it possible to observe the impact of digital policies introduced within regions and countries on the digital processes of enterprises and their interconnectedness with eco-innovation performance. According to Kesidou *et al.* (2022) and Filiou *et al.* (2023), the application of digital policies (i.e. AI, IoT) in cities that adopted strict environmental policies is often associated with the production of green patents, justifying the need for systemic coordination of the digital and environmental policies.

Several studies point to the significant sectoral differentiation in relation to the digitalisation processes (Matthess *et al.*, 2023; Bickauske *et al.*, 2020). Despite intensive technological development in R&D, the interrelationship between eco-innovations, digital transformation processes and smart technologies across individual sectors is insufficiently explored. In some studies, authors addressed this research gap by creating conceptual models

integrating multiple theoretical perspectives, such as resource-based, organisational and environmental (Rehman Khan *et al.*, 2022). When verifying their adaptability and success, a sectoral view is necessary, as well as an examination of the impact of various characteristics of enterprises affecting their successful implementation.

The listed findings supported the formulation of the following research [hypothesis 2](#).

H2. There is a significant relationship between the number of enterprises using AI for production processes and eco-innovation outcomes in the EU countries.

AI can change the way innovation is managed in enterprises by forcing the management to reconsider the enterprise innovation process. According to [Haefner *et al.* \(2021\)](#), the preferred conventional approaches to innovation management aimed at human beings have several limitations and thus, they cannot fully resolve the information needs and complexities of the innovation task. [Davenport and Ronanki \(2018\)](#) created a framework for building cognitive capabilities within enterprises to achieve their business goals. According to the authors, AI can support three important business needs: automating business processes, obtaining analytical insights through data analysis and engaging customers and employees.

[Mariani *et al.* \(2023\)](#) identified the economic, social, technological, competitive, organisational and innovation factors of AI adoption in enterprises that are ready to innovate. These authors also considered enterprise size as a potentially strong determinant of AI adoption and innovation but did not examine this determinant in their study.

[Kafetzopoulos *et al.* \(2025\)](#) state that eco-innovation strategies play a crucial role in achieving business performance through eco-innovation. Hence, it is necessary to evaluate the mediating role of digital innovations and technological mediators. Business administration processes have an important role, as they facilitate understanding and evaluation of the interactions between eco-innovation, environmental performance and business performance for achieving excellent outcomes in enterprises ([Ul-Durar *et al.*, 2023](#)). Business administration processes represent systematic activities that are necessary for an enterprise to effectively manage business operations, fulfil its obligations and promote long-term development. They include strategic, operational, support and communication processes ([Bakare *et al.*, 2024](#)). To ensure these actions, enterprises use several types of external knowledge. For instance, [Edeh and Vinces \(2024\)](#) examined the influence of various external sources of knowledge within business administration processes, significantly affecting eco-innovation in SMEs. According to the authors, external knowledge from suppliers was positively associated with eco-product and eco-process innovations. External knowledge from customers was positively associated with eco-product innovations but not with eco-process innovations. External knowledge from competitors can contribute to eco-process innovations, but not to eco-product innovations. The above-mentioned differences in effects are strongly associated with the strategic (long-term) and operational (short-term) characteristics of tasks within these processes ([Olaleye, 2023](#); [Al-Shami and Rashid, 2022](#)). [Scarpellini *et al.* \(2020a, b\)](#) found that both formal and informal environmental management systems, such as certification standards and other management and environmental accounting practices applied in the field of eco-innovation, can support the achievement of desirable eco-innovation outcomes in enterprises.

Based on these findings, we propose research [hypothesis 3](#) as follows:

H3. There is a significant relationship between the number of enterprises using AI for business administration processes and eco-innovation outcomes in the EU countries.

[Yin *et al.* \(2023\)](#) investigated the impact of AI development on green technology innovation under various intensities of environmental regulation, R&D investment and the institutional environmental threshold conditions. According to the study outcomes, AI development will support green technology innovation only if the intensity of environmental and institutional regulation surpasses certain threshold levels. Conversely, AI development, represented by the

application of industrial robots, does not have an obvious impact on green technology innovation, even if R&D investment exceeds a certain threshold.

2.2 Influence of enterprise and sector aspects on the development of AI technologies

The manufacturing sector is the strongest driver of economic development and, at the same time, the main source of environmental pollution (Jiang *et al.*, 2021). The main barriers to the development of the manufacturing sector are ecological problems and limited resources. AI can solve many production problems. Jiang *et al.* (2021) advocate the beneficial innovations of green manufacturing technology based on AI and blockchain technology. Proficiencies such as green design, green technology innovation and recycling support in creating and improving green manufacturing capabilities. Importantly, AI development and blockchain technology have changed the development models of traditional production processes and support the ecological and sustainable development of the manufacturing sector (Wang *et al.*, 2022).

Tian *et al.* (2023) analyse the action mechanism of the influence of AI on green technology innovation performance from the perspective of the efficiency and progress of green technologies. AI enables data mining and analysis (Guo *et al.*, 2023), optimisation of the process flows (Peksen, 2023; Abd Aziz *et al.*, 2021), identification of the different process levels, accurate monitoring of process quality (Prezas *et al.*, 2022), improvement in product production, reducing dependence on physical prototypes (Soori *et al.*, 2023), quick modernisation of new products, dynamic process coordination and intelligent decision support (Sikka *et al.*, 2022; Contieri *et al.*, 2024), reducing resource constraints in eco-innovations, efficiently controlling the cost of eco-innovations, reducing innovation risks and leveraging willingness to innovate ecological products. According to Bouschery *et al.* (2023), the application of large learning and language models reduces the product development cycle to make it possible to efficiently analyse innovation needs and implement the R&D of eco products, to constantly improve the innovative capabilities of green technologies and protect the environment.

Based on these outcomes, we propose research hypothesis 4.

H4. There is a significant relationship between the number of enterprises using AI for business management and Eco-innovation outcomes in the EU countries.

AI helps to resolve large-scale logistics issues in enterprises. Interest in AI use in the field of transport is influenced by the increasing demand for travelling, higher demand for quality, reliability and punctuality, CO₂ emissions, concerns about individual and social safety and environmental degradation. The AI methods that support transport include, for instance, Artificial Neural Networks (ANN), Genetic Algorithms (GA), Simulated Annealing (SA), Fuzzy Logic Model (FLM) and Ant Colony Optimizer (ACO). The goal of using these techniques in traffic management is to reduce traffic/system congestion, increase reliability, improve the economic parameters and productivity of the entire system (Iyer, 2021). As Klumpp (2018) states in his study, the lack of highly qualified personnel in regions, pressure to improve efficiency and sustainability and to create the widespread adoption of AI in business logistics systems. The design of many concepts declared in the case studies confirms the significant effects of the collaboration between human operators and AI systems (Yang and Huang, 2021). The importance of automated systems in logistics has been growing strongly, including driver and pilot jobs under autonomous control. Wilson *et al.* (2022) examined AI technologies in detail and highlighted its effects for reverse logistics within the CE. According to the author, the various functions and tasks of reverse logistics rely on individual AI forms (e.g. mechanical, analytical, intuitive).

Based on these findings, hypothesis 5 is formulated as follows:

H5. There is a significant relationship between the number of enterprises using AI for logistics and eco-innovation outcomes in the EU countries.

AI has been increasingly applied in data security management across various economic sectors. Many enterprises use AI technologies to ensure information and communication technology (ICT) security. There are many interdisciplinary intersections between cybersecurity and AI. As Li (2018) states, AI technologies have been introduced into cybersecurity, but the AI models are expected to face increasing cyber threats. The AI-based approaches to detect and defend against cyber-attacks and threats are much more effective and advanced compared to the conventional cybersecurity strategies (Zhang *et al.*, 2022). The AI models need specific cybersecurity protection technologies. Singh *et al.* (2020) highlight the lack of security metrics specific to industrial control systems and the need to develop methodologies to measure and manage the risks associated with industrial cyber threats. Although there are numerous studies on AI applications in cybersecurity and Explainable AI (EAI) employed in sectors such as healthcare, financial services and judiciary, there are currently no research studies involving EAI applications in the field of cyber protection. Zhang *et al.* (2022). Rosário and Raimundo (2021) indicate the progress in the development of AI technologies and the use of multi-level solutions to security problems. In fact, AI also has an increasing impact on security systems focused on supporting decision-making at the management level. Many expert systems are integrated into the corporate culture.

The above facts have supported the formulation of research hypothesis 6 as follows:

- H6. There is a significant relationship between the number of enterprises using AI for ICT security and eco-innovation outcomes in the EU countries.

Technological development has a significant impact on human resource management (HRM), which has become increasingly important in recruiting employees to bring knowledge and skills (Dickson and Nusair, 2010). Broadly, AI technologies engaged in recruitment represent a new field and not every enterprise uses it in the recruitment process (Johansson and Herranen, 2019). The most suitable areas for using AI in the recruitment process include pre-selection, communication with candidates and sending recruitment results to applicants. Research studies demonstrate that the main advantages of AI application in the recruitment process are accelerated quality and elimination of routine tasks (Johansson and Herranen, 2019). The application of AI in HRM is a positive signal of enterprises' readiness for adopting new technologies (Upadhyay and Khandelwal, 2018).

Based on these findings, research hypothesis 7 has been formulated as follows:

- H7. There is a significant relationship between the number of enterprises using AI for HRM or recruitment and eco-innovation outcomes in the EU countries.

The stated outcomes of the research studies confirm the defined research gap and have enabled us to formulate the elementary research question: Is there a relationship between AI adoption in enterprises between the selected business functions and green innovation outcomes in the EU countries? The solution is conditional on exploring the proposed seven research hypotheses that are supported by the outcomes of the available research studies in the previous subsections.

Although the review of research studies is not exhaustive due to the content and limitation scope of the study, their selection clearly declares the importance of the investigated issue and the multidimensional applicability of the expected outcomes.

This consistent fact is reflected in our study, which aims to quantify the relationship between AI adoption in enterprises, considering their size and green innovation outcomes, represented by the Eco-innovation Index in the EU countries. To achieve this objective, we formulated the following research question: Is there a relationship between AI adoption in enterprises between the selected business functions and green innovation outcomes in the EU countries?

This study is structured as follows. First, we discuss the importance of the interconnection of AI technologies and the eco-innovation outputs at the enterprise level. We reason the research gap and the importance of investigating the issue for the development of adoption concepts of digital technologies and policymaking. The theoretical part is linked to the

research questions, and it presents the latest research studies and their results. In the methodological section, the database, the selected analytical procedures and tools are examined. In the analytical section, the outcomes of the analyses are presented, which are suitably visualised and provide a platform for discussion. In the discussion section, the outcomes are discussed, and the conclusions are summarised. The final section presents the aggregated results and their use for policymakers.

3. Methodology

Based on the defined research questions in the first section and their theoretical reasoning in the literature review, a methodological procedure was set, as well as the methods applied for the data set.

All the European Union countries ($n = 27$) Austria (AT), Belgium (BE), Bulgaria (BG), Croatia (HR), Cyprus (CY), Czechia (CZ), Denmark (DK), Estonia (EE), Finland (FI), France (FR), Germany (DE), Greece (GR), Hungary (HU), Ireland (IE), Italy (IT), Latvia (LV), Lithuania (LT), Luxembourg (LU), Malta (MT), Netherlands (NL), Poland (PL), Portugal (PT), Romania (RO), Slovakia (SK), Slovenia (SI), Spain (ES) and Sweden (SE) are included in the analytical processing. Data from the Eurostat database (Eurostat, 2023), section AI by size class of enterprise, were processed. This data set is relatively new and, in many cases, data for 2021 were available. Therefore, our analysis focused only on 2021. Table 1 lists the AI indicators by enterprise size class.

Table 1. Variables description – enterprise use of AI technologies

Abr	Enterprises use of AI technologies	Enterprises size	Mean	CV
AI_mrkt_S	Marketing or sales	10 to 49 persons	1.777778	0.794015
AI_prod_S	Production processes	10 to 49 persons	1.314815	0.721751
AI_admin_S	Organisation of business administration processes	10 to 49 persons	1.588462	0.827997
AI_man_S	Management of enterprises	10 to 49 persons	1.292308	1.109530
AI_log_S	Logistics	10 to 49 persons	0.611111	0.976911
AI_scr_S	ICT security	10 to 49 persons	1.655556	0.874570
AI_hrm_S	Human resources management or recruiting	10 to 49 persons	0.622222	1.042819
AI_mrkt_M	Marketing or sales	50 to 249 persons	3.362963	0.737751
AI_prod_M	Production processes	50 to 249 persons	3.214815	0.666072
AI_admin_M	Organisation of business administration processes	50 to 249 persons	3.262963	0.813962
AI_man_M	Management of enterprises	50 to 249 persons	2.622222	1.227393
AI_log_M	Logistics	50 to 249 persons	1.651852	0.860469
AI_scr_M	ICT security	50 to 249 persons	4.185185	0.830267
AI_hrm_M	Human resources management or recruiting	50 to 249 persons	1.348148	0.960850
AI_mrkt_L	Marketing or sales	250 persons or more	7.770370	0.560610
AI_prod_L	Production processes	250 persons or more	9.448148	0.546203
AI_admin_L	Organisation of business administration processes	250 persons or more	8.129630	0.765535
AI_man_L	Management of enterprises	250 persons or more	5.803704	1.027246
AI_log_L	Logistics	250 persons or more	5.574074	0.721043
AI_scr_L	ICT security	250 persons or more	11.44231	0.625646
AI_hrm_L	Human resources management or recruiting	250 persons or more	3.540741	0.879552

Table 1 shows the abbreviations for individual variables and information on the percentage of enterprises using AI. From the presented data, it can be observed that the largest AI process usage rate was recorded in large enterprises, namely in ICT security and production processes. The AI indicators are presented in percentage and represent the percentage of enterprises where employees have access to the Internet. Furthermore, the variable Eco-Innovation (EII) entered the analytical processes and is interpreted as follows: the higher the value, the more intensive the eco-innovations in a specific country. The index is created based on a reference value from 2013 (EU average) equal to 100. The arithmetic average of the selected EU countries ($n = 27$) in 2021 is 110.28 ± 31.97 .

In the first step, a correlation analysis was conducted through the Pearson correlation coefficient. The purpose of this process was to interpret elementary information about the relationship between AI adoption and eco-innovation and information about the relationship between all the variables. Analytical processing was conducted using regression models and aimed at evaluating the relationship between AI use in small, medium and large enterprises with eco-innovations in EU countries. An ordinary least squares regression (OLS), an ordinary least squares regression with estimator HC0 (OLS HC0) and spatial models represented by a spatial model with lagged independent variable (SLX) and a spatial autoregressive model (SAR) were employed to assess the selected relationships. Prior to actual application of the mentioned regression models, condition tests were evaluated (Shapiro–Wilk test to assess residual normality, Breusch–Pagan test to assess the constancy of the variability of residuals – homoscedasticity and spatial Moran’s I). Cluster analysis (CA) was applied to identify the relative position of the EU countries based on the level of AI adoption across enterprises of varied sizes and their eco-innovation performance. Regarding the multidimensional characteristics of the data, CA enabled the grouping of countries with similar characteristics. This step provides a more structured interpretation of the relationships between AI integration in business processes and green innovation outcomes. The partitioning around medoids (PAM) method was selected for its robustness in addressing data with potential outliers. The Manhattan distance metric was applied as it is suitable for datasets with differing scales. The optimal number of clusters was determined using the silhouette method, ensuring a meaningful classification of countries based on their AI adoption patterns and eco-innovation performance. In the CA, standardised data were processed, from 0 to 1, where 1 represents the highest and the most positively perceived value, and 0 represents the worst value, indicating the country with the worst result. The calculations were processed in the R programming language, version 4.3.0 (R Core Team, 2023) with the help of the psych package (Revelle, 2023), spdep (Bivand, 2022), spatialreg (Pebesma and Bivand, 2023), cluster (Maechler *et al.*, 2022) and factoextra (Kassambara and Mundt, 2020).

4. Results

This section focused on illustrating the results and providing a brief interpretation of the outcomes of individual analytical procedures. Figure 1 presents the bivariate relationships that describe the relations between the selected indicators through the Pearson r correlation coefficient. Above the diagonal line, there is the coefficient itself, and the p values are listed below this line. Considering the research goal, it is important to examine the relationship of the selected indicators of AI adoption with the Eco-innovation index.

As observed in Figure 1, a significant relationship did not appear in small enterprises in several cases. The relationship level is highlighted in colour, where the darker the colour, the stronger the relationship. The interconnections between the AI adoption indicators demonstrate the relatively large interconnectedness among themselves. From the above, it can be interpreted that where a high proportion of AI adoption is in a certain area, for instance, in small enterprises, there will be a high proportion of AI adoption in the other areas of SMEs.

Further analytical processes focused on demonstrating the relationships between the selected areas of AI use in small, medium and large enterprises. Several regression models

Pearson r	EI	AI_mkt_S	AI_prod_S	AI_admin_S	AI_man_S	AI_log_S	AI_scr_S	AI_hm_S	AI_mkt_M	AI_prod_M	AI_admin_M	AI_man_M	AI_log_M	AI_scr_M	AI_hm_M	AI_mkt_L	AI_prod_L	AI_admin_L	AI_man_L	AI_log_L	AI_scr_L	AI_hm_L
EI		.327	.443	.436	.365	.369	.275	.232	.563	.445	.540	.430	.495	.408	.417	.696	.719	.605	.496	.695	.638	.532
AI_mkt_S	.096		.883	.859	.822	.789	.643	.820	.900	.815	.808	.636	.656	.709	.877	.585	.540	.497	.502	.519	.550	.483
AI_prod_S	.021	.000		.909	.841	.911	.723	.801	.894	.856	.859	.712	.826	.785	.897	.710	.677	.657	.649	.729	.718	.615
AI_admin_S	.026	.000	.000		.869	.879	.638	.867	.842	.726	.910	.752	.806	.695	.914	.654	.620	.711	.657	.691	.629	.643
AI_man_S	.067	.000	.000	.000		.866	.700	.817	.782	.722	.731	.910	.756	.755	.834	.627	.554	.561	.814	.672	.617	.514
AI_log_S	.058	.000	.000	.000	.000		.725	.866	.783	.811	.795	.820	.863	.793	.899	.683	.652	.696	.746	.729	.693	.633
AI_scr_S	.165	.000	.000	.000	.000	.000		.561	.652	.814	.591	.600	.585	.938	.652	.564	.542	.396	.555	.547	.804	.425
AI_hm_S	.244	.000	.000	.000	.000	.000	.002		.754	.652	.751	.703	.703	.617	.879	.563	.463	.575	.578	.512	.514	.566
AI_mkt_M	.002	.000	.000	.000	.000	.000	.000	.000		.860	.905	.682	.727	.739	.896	.812	.754	.716	.629	.737	.758	.712
AI_prod_M	.020	.000	.000	.000	.000	.000	.000	.000	.000		.777	.654	.714	.877	.813	.747	.748	.596	.607	.682	.811	.594
AI_admin_M	.004	.000	.000	.000	.000	.000	.001	.000	.000	.000		.691	.815	.694	.903	.778	.788	.860	.635	.762	.737	.782
AI_man_M	.025	.000	.000	.000	.000	.001	.000	.000	.000	.000	.000		.808	.663	.768	.681	.653	.712	.952	.750	.638	.652
AI_log_M	.009	.000	.000	.000	.000	.001	.000	.000	.000	.000	.000	.000		.700	.826	.776	.708	.813	.796	.783	.730	.753
AI_scr_M	.035	.000	.000	.000	.000	.000	.001	.000	.000	.000	.000	.000	.000		.750	.655	.631	.511	.613	.645	.857	.483
AI_hm_M	.031	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000		.722	.685	.743	.664	.684	.688	.723
AI_mkt_L	.000	.001	.000	.000	.001	.000	.002	.002	.000	.000	.000	.000	.000	.000	.000		.900	.841	.767	.904	.872	.836
AI_prod_L	.000	.004	.000	.001	.003	.000	.003	.015	.000	.000	.000	.000	.000	.000	.000	.000		.878	.731	.911	.857	.812
AI_admin_L	.001	.008	.000	.000	.003	.000	.041	.002	.000	.001	.000	.000	.000	.006	.000	.000	.000		.762	.874	.738	.900
AI_man_L	.009	.008	.000	.000	.000	.000	.003	.002	.000	.001	.000	.000	.000	.001	.000	.000	.000	.000		.843	.710	.730
AI_log_L	.000	.006	.000	.000	.000	.000	.003	.006	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000		.850	.793
AI_scr_L	.000	.004	.000	.001	.001	.000	.000	.007	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000		.754
AI_hm_L	.004	.011	.001	.000	.007	.000	.027	.002	.000	.001	.000	.000	.000	.011	.000	.000	.000	.000	.000	.000	.000	

Figure 1. Correlation matrix of selected indicators

were applied to evaluate the mentioned relationships to minimise statistical errors. Tables 2–8 are divided vertically into three sections according to enterprise size: small enterprises with up to 49 employees (small), medium-sized enterprises with 50–249 employees (medium) and large enterprises with more than 250 employees (large). The dependent variable in these processes was represented by the eco-innovation level. The horizontal direction demonstrates the individual applied models (OLS, OLS HC0, SLX and SAR). A stable result can be considered when the outcomes of the individual models do not differ from each other in the statistical significance of the relationship direction.

Table 2 shows the outcomes of the relationship evaluation between the adoption of AI technologies in marketing or sales in small, medium and large enterprises (independent variable) and eco-innovation (dependent variable). When focusing on small enterprises (the Small section in the table), it seems that the mentioned relationship cannot be considered significant. If we focus on medium enterprises (the Medium section of the table), we can confirm a significant relationship. Based on β coefficients, this is a positive relationship, indicating that the growth of the share of enterprises that use AI technologies in marketing or sales can be associated with a higher rate of eco-innovation. A similar outcome can also be observed for large enterprises (the Large section of the table). In large enterprises, the relationship between the adoption of AI technologies in marketing and eco-innovation appears significant, while its direction is positive. Where there were higher ratios of AI technologies in marketing or sales in large enterprises, the values for eco-innovation were also higher. From the perspective of relationship closeness, based on the coefficient of determination, there is a closer relationship between the adoption of AI technologies in marketing or sales and eco-innovation in large enterprises.

Table 3 presents the results of the assessment of the relationships between the adoption of AI technologies in the production processes in small, medium and large enterprises (independent variable) and eco-innovation (dependent variable). The outcomes of the

Table 2. Interconnectedness of AI technologies in marketing or sales and eco-innovation (**Hypothesis 1**)

Size	Coef	OLS	OLS HC0	SLX	SAR
Small	(Intercept)	97.123 [9.649] <0.001	97.123 [9.091] <0.001	100.917 [22.704] <0.001	95.543 [37.233] 0.010
	AI_mrkt_S	7.398 [4.282] 0.096	7.398 [4.763] 0.133	7.155 [4.559] 0.130	7.381 [4.130] 0.074
	lag.AI_mrkt_S	–	–	–1.981 [10.684] 0.854	–
	rho	–	–	–	0.015 [0.324] 0.962
	R ²	0.107/0.071	–	0.108/0.034	–
	Shapiro–Wilk	W = 0.9609, <i>p</i> -value = 0.3873			
	Breusch–Pagan	BP = 0.90379, <i>df</i> = 1, <i>p</i> -value = 0.3418			
Medium	(Intercept)	85.889 [8.846] <0.001	85.889 [7.769] <0.001	72.184 [21.120] 0.002	94.491 [36.200] 0.009
	AI_mrkt_S	7.252 [2.131] 0.002	7.252 [2.227] 0.003	7.513 [2.182] 0.002	7.327 [2.053] <0.001
	lag.AI_mrkt_S	–	–	4.143 [5.785] 0.481	–
	rho	–	–	–	–0.085 [0.321] 0.791
	R ²	0.317/0.289	–	0.331/0.275	–
	Shapiro–Wilk	W = 0.98589, <i>p</i> -value = 0.9647			
	Breusch–Pagan	BP = 1.2148, <i>df</i> = 1, <i>p</i> -value = 0.2704			
Large	(Intercept)	70.571 [9.346] <0.001	70.571 [7.066] <0.001	59.986 [30.443] 0.060	68.410 [34.005] 0.044
	AI_mrkt_L	5.110 [1.054] <0.001	5.110 [0.747] <0.001	5.177 [1.088] <0.001	5.106 [1.016] <0.001
	lag.AI_mrkt_L	–	–	1.408 [3.847] 0.718	–
	rho	–	–	–	0.021 [0.301] 0.944
	R ²	0.485/0.464	–	0.488/0.445	–
	Shapiro–Wilk	W = 0.95985, <i>p</i> -value = 0.3666			
	Breusch–Pagan	BP = 0.018869, <i>df</i> = 1, <i>p</i> -value = 0.8907			
Moran I	Moran I = 0.27939, <i>p</i> -value = 0.39				

analytical processes are significant across all three types of enterprises. In SMEs, the results are significant at the $\alpha < 0.05$ level. In the case of large enterprises (the Large section of the table), the relationship is significant at the $\alpha < 0.001$ level. In all these cases, this is a positive relationship, indicating that with the growth of AI technologies in the production process indicator, the growth of eco-innovation can also be expected. From the perspective of the coefficient of determination, in SMEs, this value was approximately 20% of the variability; however, in large enterprises, it was approximately 50% of the variability.

Table 4 presents the outcomes of the analytical processes aimed at evaluating the relationships between the adoption of AI technologies in the organisation of business administration processes in small, medium and large enterprises (independent variable) and eco-innovation (dependent variable). The outcomes of the analytical processes appear to be statistically significant across all three types of enterprises. In small enterprises, the results are significant at the $\alpha < 0.05$ level. Nevertheless, in the case of medium and large enterprises, the interconnection is significant at the $\alpha < 0.001$ level. In all the cases, this is a positive relationship, indicating that with the growth of AI technologies in the organisation of the business administration processes indicator, eco-innovation growth can be expected at the

Table 3. Interconnectedness of AI technologies in the production processes and eco-innovation (Hypothesis 2)

Size	Coef	OLS	OLS HC0	SLX	SAR
Small	(Intercept)	90.673 [9.736] <0.001	90.673 [8.151] <0.001	90.535 [22.873] <0.001	90.658 [36.319] 0.013
	AI_prod_S	14.909 [6.043] 0.021	14.909 [5.536] 0.012	14.919 [6.334] 0.027	14.909 [5.831] 0.011
	lag.AI_prod_S	–	–	0.106 [15.842] 0.995	–
	rho	–	–	–	0.000 [0.319] 1.000
	R ² Adj.	0.196/0.164	–	0.196/0.129	–
	Shapiro–Wilk	W = 0.94518, p-value = 0.1635			
	Breusch–Pagan	BP = 0.49518, df = 1, p-value = 0.4816			
Moran I	Moran I = 0.3792, p-value = 0.3523				
Medium	(Intercept)	88.898 [10.269] <0.001	88.898 [9.371] <0.001	88.727 [27.338] 0.003	89.658 [37.216] 0.016
	AI_prod_M	6.650 [2.674] 0.020	6.650 [2.446] 0.012	6.655 [2.853] 0.028	6.655 [2.584] 0.010
	lag.AI_prod_M	–	–	0.050 [7.387] 0.995	–
	rho	–	–	–	–0.007 [0.321] 0.981
	R ² Adj.	0.198/0.166	–	0.198/0.132	–
	Shapiro–Wilk	W = 0.94907, p-value = 0.2035			
	Breusch–Pagan	BP = 0.0178, df = 1, p-value = 0.8939			
Moran I	Moran I = 0.34517, p-value = 0.365				
Large	(Intercept)	68.159 [9.225] <0.001	68.159 [6.881] <0.001	51.499 [20.787] 0.021	83.982 [32.228] 0.009
	AI_prod_L	4.458 [0.861] <0.001	4.458 [0.722] <0.001	4.447 [0.864] <0.001	4.527 [0.823] <0.001
	lag.AI_prod_L	–	–	1.973 [2.204] 0.380	–
	rho	–	–	–	–0.158 [0.291] 0.587
	R ² Adj.	0.518/0.498	–	0.533/0.494	–
	Shapiro–Wilk	W = 0.98223, p-value = 0.909			
	Breusch–Pagan	BP = 0.88114, df = 1, p-value = 0.3479			
Moran I	Moran I = –1.0302, p-value = 0.8486				

same time. From the perspective of the coefficient of determination, this value was explained approximately at the 20% level of variability in small enterprises, at 30% level in medium-sized enterprises and up to 40% variability was reached in large enterprises.

Table 5 shows the outcomes of the analytical processes focused on assessing the relationships between the adoption of AI technologies in the management of enterprises of all size classes (independent variable) and eco-innovation (dependent variable). First, the outcomes of small enterprises were evaluated (the Small section of the table). Based on the condition tests, the OLS model is appropriate, but its output did not reach a significant level at the $\alpha < 0.05$ level (OLS: p -value = 0.067, $\beta = 7.803$). For the OLS HC0 estimator and the spatial SAR model, the output are significant. A certain level of instability can be deduced from the above. Hence, the hypothesis of a meaningful relationship was rejected. A meaningful relationship was evident in medium and large enterprises. This is a positive relationship, indicating that with the growth of AI technologies in the management of the enterprise indicator, eco-innovation growth can also be expected. The outcomes of the coefficient of determination in all three types of enterprises by size acquire a coefficient of determination lower than 30%. The highest occurred in large enterprises (OLS $R^2 = 0.246$).

Table 4. Interconnectedness of AI technologies in business administration processes and eco-innovation (Hypothesis 3)

Size	Coef	OLS	OLS HC0	SLX	SAR
Small	(Intercept)	92.358 [9.201] <0.001	92.358 [7.948] <0.001	82.544 [23.277] 0.002	88.315 [36.031] 0.014
	AI_admin_S	10.663 [4.497] 0.026	10.663 [4.599] 0.029	11.333 [4.798] 0.027	10.654 [4.335] 0.014
	lag.AI_admin_S	–	–	5.888 [12.788] 0.650	–
	rho	–	–	–	0.039 [0.317] 0.902
	R ² Adj.	0.190/0.156	–	0.197/0.127	–
	Shapiro–Wilk	W = 0.9543, p-value = 0.2917			
	Breusch–Pagan	BP = 1.0044, df = 1, p-value = 0.3163			
Medium	(Intercept)	89.079 [8.465] <0.001	89.079 [7.084] <0.001	77.837 [18.506] <0.001	91.670 [35.101] 0.009
	AI_admin_M	6.496 [2.027] 0.004	6.496 [2.225] 0.007	6.667 [2.064] 0.004	6.511 [1.953] <0.001
	lag.AI_admin_M	–	–	3.525 [5.145] 0.500	–
	rho	–	–	–	–0.025 [0.311] 0.935
	R ² Adj.	0.291/0.263	–	0.305/0.247	–
	Shapiro–Wilk	W = 0.97635, p-value = 0.7724			
	Breusch–Pagan	BP = 2.5995, df = 1, p-value = 0.1069			
Large	(Intercept)	85.017 [8.320] <0.001	85.017 [5.663] <0.001	68.838 [18.421] 0.001	85.416 [33.560] 0.011
	AI_admin_L	3.107 [0.818] <0.001	3.107 [0.690] <0.001	2.985 [0.828] 0.001	3.108 [0.789] <0.001
	lag.AI_admin_L	–	–	2.447 [2.485] 0.335	–
	rho	–	–	–	–0.004 [0.309] 0.990
	R ² Adj.	0.366/0.340	–	0.390/0.340	–
	Shapiro–Wilk	W = 0.9683, p-value = 0.5575			
	Breusch–Pagan	BP = 1.7996, df = 1, p-value = 0.1798			
Moran I	Moran I = –0.091669, p-value = 0.5365				

Table 6 presents the outcomes of the analytical processes aimed at assessing the relationships between the adoption of AI technologies in logistics in small, medium and large enterprises (independent variable) and eco-innovation (dependent variable). Even in this case, a certain instability is evident for small enterprises (the Small section of the table), as the selected analytical approaches present different results from the perspective of significant relationships. Based on the condition tests, the OLS model is suitable, but its output does not reach a significant level at the $\alpha < 0.05$ level (OLS: p val = 0.058, $\beta = 19.761$). For the OLS HC0 estimator and the spatial SAR model, the output is significant. This justifies the hypothesis rejection for a significant relationship. Moreover, a noteworthy relationship was evident in medium and large enterprises. This is a positive relationship, indicating that with the growth of AI technologies in the logistics indicator, the growth of eco-innovation can also be expected. From the perspective of the coefficient of determination, the closest connection was manifested in large enterprises, where approximately 48% of the variability was explained.

Table 5. Interconnectedness of AI technologies in the management of enterprises and eco-innovation (Hypothesis 4)

Size	Coef	OLS	OLS HCO	SLX	SAR
Small	(Intercept)	102.285 [7.761]	102.285 [6.355]	115.758 [19.141]	118.301
		<0.001	<0.001	<0.001	[39.018] 0.002
	AI_man_S	7.803 [4.064]	7.803 [2.979]	6.975 [4.237]	8.176 [3.894]
		0.067	0.015	0.113	0.036
	lag.AI_man_S	–	–	–10.650 [13.808]	–
				0.448	
	rho	–	–	–	–0.152 [0.343]
				0.656	
	R ² Adj.	0.133/0.097	–	0.155/0.082	–
	Shapiro–Wilk	W = 0.94282, p-value = 0.1568			
	Breusch–Pagan	BP = 0.088403, df = 1, p-value = 0.7662			
	Moran I	Moran I = 0.16845, p-value = 0.4331			
Medium	(Intercept)	99.074 [7.363]	99.074 [6.279]	89.535 [26.704]	104.782
		<0.001	<0.001	0.003	[37.844] 0.006
	AI_man_M	4.272 [1.794]	4.272 [0.918]	4.460 [1.894]	4.314 [1.726]
		0.025	<0.001	0.027	0.012
	lag.AI_man_M	–	–	4.311 [11.583]	–
				0.713	
	rho	–	–	–	–0.056 [0.343]
				0.871	
	R ² Adj.	0.185/0.152	–	0.190/0.122	–
	Shapiro–Wilk	W = 0.94775, p-value = 0.189			
	Breusch–Pagan	BP = 0.084991, df = 1, p-value = 0.7706			
	Moran I	Moran I = 0.16763, p-value = 0.4334			
Large	(Intercept)	94.851 [7.677]	94.851 [6.535]	61.987 [27.524]	100.775
		<0.001	<0.001	0.034	[37.511] 0.007
	AI_man_L	2.658 [0.932]	2.658 [0.741]	2.895 [0.941]	2.679 [0.896]
		0.009	0.001	0.005	0.003
	lag.AI_man_L	–	–	6.732 [5.419]	–
				0.226	
	rho	–	–	–	–0.058 [0.341]
				0.865	
	R ² Adj.	0.246/0.215	–	0.291/0.232	–
	Shapiro–Wilk	W = 0.94908, p-value = 0.2037			
	Breusch–Pagan	BP = 0.048472, df = 1, p-value = 0.8257			
	Moran I	Moran I = –0.032911, p-value = 0.5131			

Table 7 presents the results of the evaluation of relationships and the adoption of AI technologies in marketing or sales in small, medium and large enterprises (independent variable) and eco-innovation (dependent variable). From the outcomes obtained for small enterprises (the Small section of the table), the mentioned relationship cannot be considered significant. In medium-sized enterprises (the Medium section of the table), a significant relationship is evident. Based on the β coefficients, this is a positive relationship, indicating that the growth of the share of enterprises using AI technologies in marketing or sales can be associated with a higher rate of eco-innovation. Similar results can also be observed for large enterprises (the Large section of the table). In large enterprises, the relationship between the adoption of AI technologies in marketing and eco-innovation appears e significant, while its direction is positive. There were higher values for eco-innovation, where higher ratios of AI technologies in marketing or sales in large enterprises were observed. Based on the coefficient of determination, a closer relationship between the adoption of AI technologies in marketing or sales and eco-innovation in large enterprises was observed from the perspective of relationship closeness.

Table 6. Interconnectedness of AI technologies in logistics and eco-innovation (*Hypothesis 5*)

Size	Coef	OLS	OLS HC0	SLX	SAR
Small	(Intercept)	98.199 [8.428] <0.001	98.199 [6.379] <0.001	103.375 [25.745] <0.001	93.845 [36.596] 0.010
	AI_log_S	19.761 [9.955] 0.058	19.761 [6.053] 0.003	18.853 [11.008] 0.100	19.706 [9.599] 0.040
	lag.AI_log_S	–	–	–8.615 [40.399] 0.833	–
	rho	–	–	–	0.042 [0.324] 0.897
	R ² Adj.	0.136/0.102	–	0.138/0.066	–
	Shapiro–Wilk	W = 0.95956, p-value = 0.3611			
	Breusch–Pagan	BP = 0.062897, df = 1, p-value = 0.802			
Medium	(Intercept)	91.899 [8.454] <0.001	91.899 [6.874] <0.001	92.996 [29.399] 0.004	84.512 [35.460] 0.017
	AI_log_M	11.125 [3.910] 0.009	11.125 [2.731] <0.001	11.084 [4.125] 0.013	11.117 [3.763] 0.003
	lag.AI_log_M	–	–	–0.715 [18.309] 0.969	–
	rho	–	–	–	0.071 [0.316] 0.822
	R ² Adj.	0.245/0.214	–	0.245/0.182	–
	Shapiro–Wilk	W = 0.92112, p-value = 0.04201			
	Breusch–Pagan	BP = 0.0013101, df = 1, p-value = 0.9711			
Large	(Intercept)	79.442 [7.807] <0.001	79.442 [6.503] <0.001	63.329 [19.534] 0.003	85.404 [33.372] 0.010
	AI_log_L	5.532 [1.143] <0.001	5.532 [1.188] <0.001	5.567 [1.148] <0.001	5.553 [1.100] <0.001
	lag.AI_log_L	–	–	3.304 [3.670] 0.377	–
	rho	–	–	–	–0.058 [0.305] 0.848
	R ² Adj.	0.484/0.463	–	0.500/0.459	–
	Shapiro–Wilk	W = 0.97362, p-value = 0.6991			
	Breusch–Pagan	BP = 1.9859, df = 1, p-value = 0.1588			
Moran I	Moran I = –0.40411, p-value = 0.6569				

Table 8 presents the results of the regression analysis focused on the relationship between the adoption of AI technologies in human resources management or recruiting in small, medium and large enterprises (independent variable) and eco-innovation (dependent variable). When focusing on small businesses (the Small section of the table), it is evident that the mentioned relationship cannot be considered significant; however, it is possible to state a significant relationship in the case of medium and large enterprises. Based on the β coefficients, it is a positive relationship; for instance, the growth of the share of medium and large enterprises that use AI technologies in human resources management or recruiting can be associated with a higher rate of eco-innovation. From the perspective of anxiety in the relationship, based on the coefficient of determination, the closest relationship between the adoption of AI technologies in human resources management or recruiting and eco-innovation was found in large enterprises.

Table 7. Interconnectedness of AI technologies in ICT security and eco-innovation (Hypothesis 6)

Size	Coef	OLS	OLS HCO	SLX	SAR
Small	(Intercept)	100.221 [9.264] <0.001	100.221 [8.460] <0.001	101.596 [23.128] <0.001	98.507 [37.417] 0.008
	AI_scr_S	6.073 [4.246] 0.165	6.073 [3.841] 0.126	6.003 [4.463] 0.191	6.052 [4.089] 0.139
	lag.AI_scr_S	–	–	–0.802 [12.308] 0.949	–
	rho	–	–	–	0.017 [0.328] 0.959
	R ² Adj.	0.076/0.039	–	0.076/–0.001	–
	Shapiro–Wilk	W = 0.94683, p-value = 0.1794			
	Breusch–Pagan	BP = 0.014448, df = 1, p-value = 0.9043			
Medium	(Intercept)	94.558 [9.069] <0.001	94.558 [8.077] <0.001	100.838 [19.492] <0.001	93.963 [36.197] 0.009
	AI_scr_M	3.756 [1.680] 0.035	3.756 [1.517] 0.020	3.716 [1.713] 0.040	3.753 [1.617] 0.020
	lag.AI_scr_M	–	–	–1.532 [4.187] 0.718	–
	rho	–	–	–	0.006 [0.319] 0.986
	R ² Adj.	0.167/0.133	–	0.171/0.102	–
	Shapiro–Wilk	W = 0.95168, p-value = 0.2354			
	Breusch–Pagan	BP = 0.072877, df = 1, p-value = 0.7872			
Large	(Intercept)	76.495 [9.492] <0.001	76.495 [8.393] <0.001	54.119 [24.858] 0.040	80.382 [34.565] 0.020
	AI_scr_L	2.867 [0.707] <0.001	2.867 [0.729] <0.001	2.886 [0.708] <0.001	2.873 [0.679] <0.001
	lag.AI_scr_L	–	–	2.091 [2.147] 0.340	–
	rho	–	–	–	–0.038 [0.311] 0.902
	R ² Adj.	0.406/0.382	–	0.430/0.380	–
	Shapiro–Wilk	W = 0.96855, p-value = 0.586			
	Breusch–Pagan	BP = 1.1232, df = 1, p-value = 0.2892			
Moran I	Moran I = –0.27464, p-value = 0.6082				

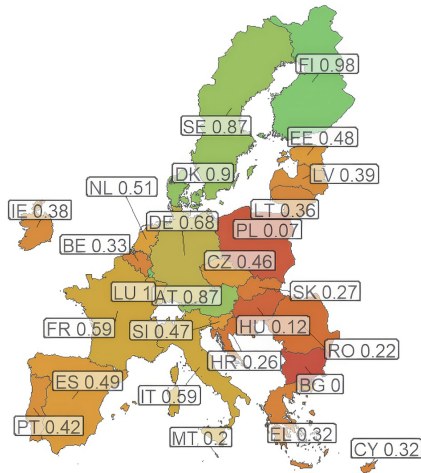
The following analytical processes are aimed at evaluating the position of the EU countries. For this reason, cluster analysis was used. Standardised variables were used in the cluster analysis. The output of the standardisation was four new variables. The first is eco-innovation, which is a variable that was not subject to any other modifications, except standardisation. The other three variables were standardised in the first step and then averaged. These three indicators (AI small enterprises, AI medium enterprises, AI large enterprises) represent the degree of adoption of artificial intelligence in enterprises by size. That is, for example, large enterprises represent the average of all the standardised variables (AI_mrkt_L, AI_prod_L, AI_admin_L, AI_man_L, AI_log_L, AI_scr_L, AI_hrm_L) of large enterprises.

Table 8. Interconnectedness of AI technologies in human resources management or recruiting and eco-innovation (Hypothesis 7)

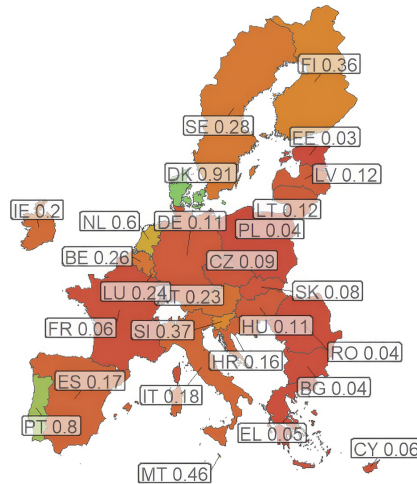
Size	Coef	OLS	OLS HC0	SLX	SAR
Small	(Intercept)	103.161 [8.534] <0.001	103.161 [7.264] <0.001	117.420 [37.223] 0.004	96.959 [37.063] 0.009
	AI_hrm_S	11.434 [9.586] 0.244	11.434 [9.015] 0.216	8.054 [12.988] 0.541	11.386 [9.237] 0.218
	lag.AI_hrm_S	–	–	–20.285 [51.494] 0.697	–
	rho	–	–	–	0.060 [0.324] 0.854
	R ² Adj.	0.054/0.016	–	0.060/–0.018	–
	Shapiro–Wilk	W = 0.96167, p-value = 0.4031			
	Breusch–Pagan	BP = 0.51666, df = 1, p-value = 0.4723			
Medium	(Intercept)	96.404 [8.314] <0.001	96.404 [6.819] <0.001	71.827 [22.060] 0.003	97.861 [37.139] 0.008
	AI_hrm_M	10.290 [4.487] 0.031	10.290 [3.853] 0.013	12.075 [4.690] 0.017	10.309 [4.330] 0.017
	lag.AI_hrm_M	–	–	18.883 [15.722] 0.241	–
	rho	–	–	–	–0.014 [0.330] 0.966
	R ² Adj.	0.174/0.141	–	0.221/0.156	–
	Shapiro–Wilk	W = 0.96039, p-value = 0.3772			
	Breusch–Pagan	BP = 0.37203, df = 1, p-value = 0.5419			
Large	(Intercept)	90.950 [8.134] <0.001	90.950 [6.846] <0.001	82.203 [14.716] <0.001	94.605 [34.222] 0.006
	AI_hrm_L	5.458 [1.739] 0.004	5.458 [1.726] 0.004	4.955 [1.891] 0.015	5.477 [1.690] 0.001
	lag.AI_hrm_L	–	–	3.571 [4.985] 0.481	–
	rho	–	–	–	–0.036 [0.319] 0.911
	R ² Adj.	0.283/0.254	–	0.298/0.239	–
	Shapiro–Wilk	W = 0.97717, p-value = 0.7935			
	Breusch–Pagan	BP = 1.0182, df = 1, p-value = 0.3129			
Moran I	Moran I = 0.022857, p-value = 0.4909				

Figure 2 presents information on the outcomes of the monitored indicators (eco-innovation, AI adoption by small businesses, AI adoption by medium-sized enterprises and AI adoption by large enterprises) in the individual EU countries. This figure comprises four maps with country shading ranging from red to green. The closer the value is to 0, the red shading increases; conversely, the closer the value is to 1, the greener the shading is. Thus, the greener the country, the more positively it is perceived compared to the other countries. These insights contribute to a more comprehensive understanding of the CA outcomes presented below. A closer look at eco-innovation reveals that the top-performing EU countries include Luxembourg, the Nordic countries and Austria. Conversely, countries ranked at the bottom include Bulgaria, Poland, Hungary and Romania. In relation to AI adoption in enterprises, Denmark exhibits the second-

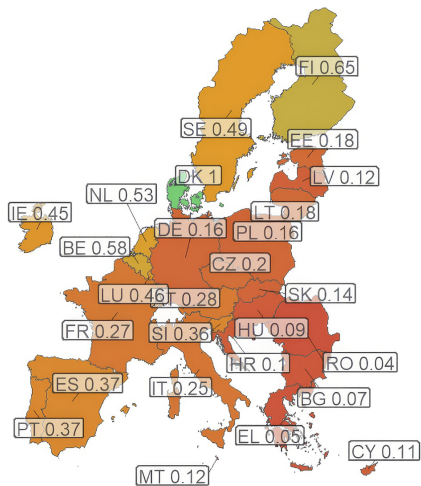
Eco-innovation



AI by small businesses



AI by large enterprises



AI by medium-sized enterprises

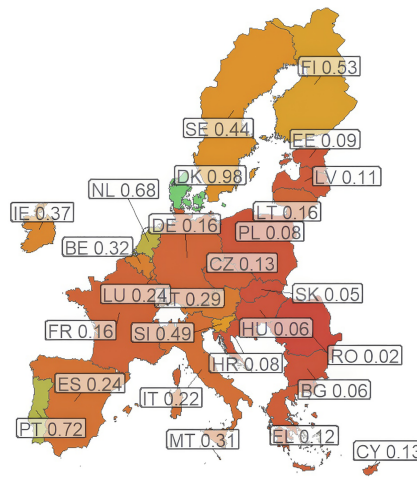


Figure 2. EU maps – Eco-innovation, AI adoption by small businesses, AI adoption by medium-sized enterprises and AI adoption by large enterprises

highest performance among all the EU countries. When interpreting AI adoption levels in small, medium and large enterprises, it can be noted that in most countries, the adoption rate is low compared to the leader (Denmark). Besides, Denmark and Portugal are prominent in SMEs. Nevertheless, Denmark’s performance is consistently dominant across all three enterprise size categories. Focusing on the lowest AI adoption rates, attention should once again be directed to the Southeastern and Central European countries.

The application of CA in this study serves as a crucial methodological approach to understanding the relationships between AI adoption and eco-innovation outcomes among all the EU countries. While the regression models provide insights into individual associations,

they do not account for the broader structural differences across national economies. Regarding the diversity of AI adoption rates in small, medium and large enterprises, as well as the significant variations in eco-innovation performance, CA allows us to identify natural clusters of countries with similar characteristics. By employing PAM method, we aimed to enhance the robustness of the clustering process, particularly given the presence of potential outliers that could distort the traditional k-means clustering outcomes. The use of the Manhattan distance metric was justified by its ability to address the differences between AI adoption variables and eco-innovation indices, ensuring that no single variable disproportionately influenced the clustering outcome. The number of clusters was determined using the silhouette method, optimising the balance between intra-cluster cohesion and inter-cluster division. This classification approach provides a clear and comparative perspective on country-level AI integration and its relation to eco-innovation performance, highlighting patterns that may not be evident through the regression analysis itself. Cluster-based findings contribute to a more nuanced understanding of how AI adoption strategies vary across the EU economies and offer actionable insights for policymakers seeking to foster digital transformation and sustainable innovation.

Figure 3 visualises the position of EU countries in the field of interconnection of AI small enterprises and eco-innovation. The closer the countries are to the lower left corner, the worse their position is compared to other countries. Alternatively, the closer a country is to the upper right corner, the better its position relative to other countries. Bulgaria and Poland occupy the worst position compared to the other EU countries, whereas Denmark, Finland and Luxembourg have a positive position towards the other EU countries. From this visualization, it is also possible to find out the position of countries within individual indicators. Among countries with the highest rate of eco-innovation, Luxembourg is positioned highest, followed by Finland and Denmark. In terms of eco-innovations, Bulgaria lags significantly, followed by Poland and Romania. Denmark, Portugal and the Netherlands dominate the number of small businesses with adapted AI technologies and several countries located at the bottom of the second cluster seem to lag.

Figure 4 demonstrates the position of EU countries in relation to the use of AI by medium-sized enterprises and eco-innovation. It can be observed that Bulgaria and Poland acquired the worst position in relation to other EU countries, whereas Denmark, Finland and Luxembourg have the most positive position. From this visualisation, it is also possible to evaluate the position of countries within individual indicators. Denmark, Portugal and the Netherlands

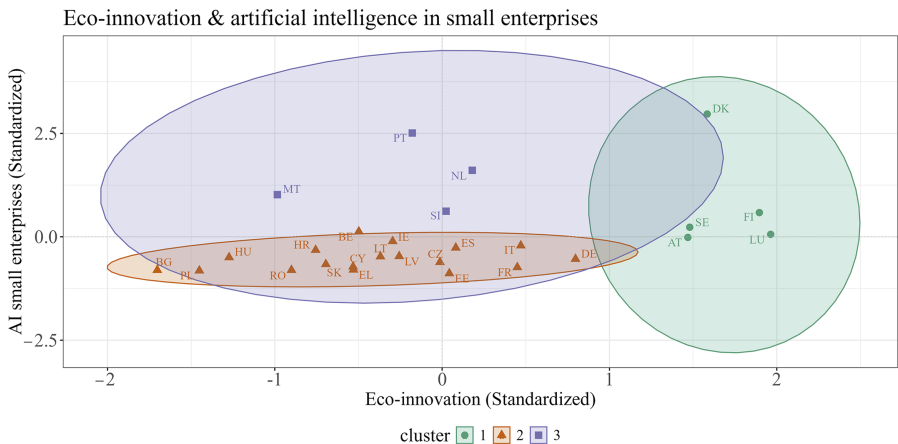


Figure 3. Cluster map: position of EU countries in the connection of the use of AI by small businesses and eco-innovation

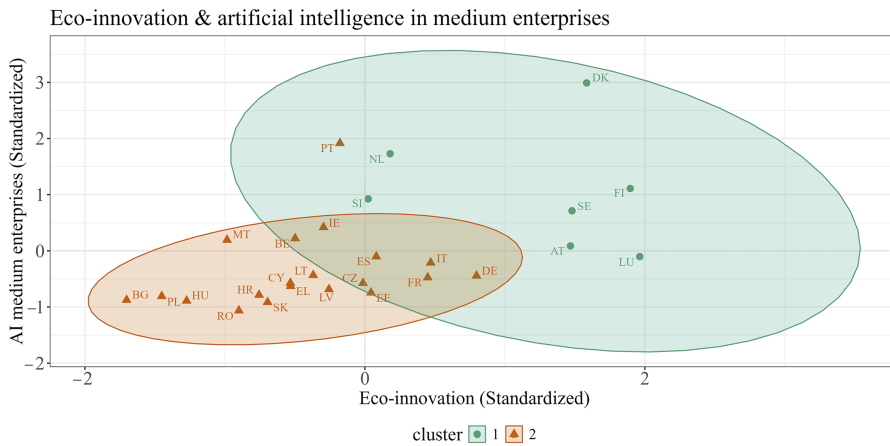


Figure 4. Cluster map: position of EU countries in relation to the use of AI by medium-sized enterprises and eco-innovation

dominate the number of small enterprises with adapted AI technologies and several countries listed in the lower part of the second cluster seem to lag. Overall, countries of the first cluster can be perceived more positively than countries of the second cluster.

Figure 5 illustrates the position of the EU countries in relation to the use of AI by large enterprises and eco-innovation. A certain similarity of the outcomes with medium-sized enterprises, or a slight similarity with small enterprises, is evident. Bulgaria, Poland and Hungary acquired the worst position compared to the other EU countries, whereas Denmark, Finland and Luxembourg show the most positive position. When evaluating the position of EU countries within the examined indicators, both positive and negative positions were evident. For example, the number of small businesses with adapted AI technologies is dominated by Denmark, Portugal, Belgium and the Netherlands; several countries listed in the lower part of the second cluster seem to lag, including Romania and Greece.

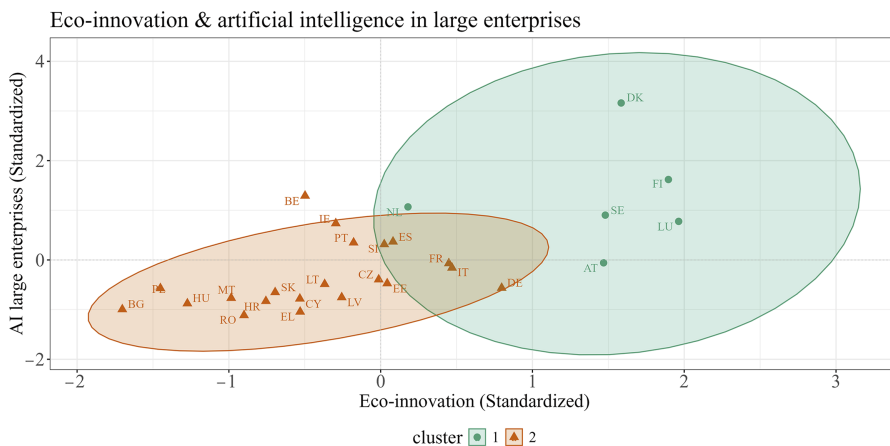


Figure 5. Cluster map: Position of EU countries in relation to the use of AI by large enterprises and eco-innovation

5. Discussion

This study aims to quantify the relationships between AI adoption in enterprises regarding their size and green innovation outputs, as represented by the eco-innovation index in the EU countries. Achieving this goal was supported by the proposed hypothesis, focused on the various sectoral dimensions or business processes. Interesting results were achieved by applying the appropriate analytical methods.

Hypothesis 1 focused on evaluating the interconnection between the adoption of AI technologies in marketing or sales and eco-innovation in the EU countries. Based on the results of applied regression models, a significant relationship can be confirmed between the investigated indicators in medium and large enterprises. Small enterprises did not manifest sufficient statistical significance. Across all the cases, a positive relationship is observed, which can be interpreted as a higher share of medium-sized, especially large enterprises using AI technologies in marketing or sales, is associated with a higher outcome of eco-innovation. These results are consistent with the findings reported by [Luo et al. \(2021\)](#), [Paschen et al. \(2021\)](#) and [Schiele and Torn \(2020\)](#), who confirm the importance of using AI technologies in the marketing and business processes, in supporting the relations between buyers and sellers, streamlining contract negotiations, among others. The digital data sources and information from social media are also related to the marketing activities, which use AI technologies and improve the decision-making processes and the overall performance of enterprises and their competitiveness. The complexity of the processes in medium-sized and large enterprises predetermines a higher level of usability of AI technologies in the marketing and sales processes.

As a part of **hypothesis 2**, the interconnection between the adoption of AI technologies in the production processes and eco-innovation outputs in the EU countries was evaluated. The outcomes of the regression models confirmed the presence of a significant relationship between these indicators in small, medium and large enterprises. In all these cases, a positive relationship exists, indicating that a higher level of enterprises engaged in using AI technologies in production processes is associated with a higher eco-innovation output. The closest relationship was found in large enterprises. These results are also confirmed by numerous research studies, which justify the strong significance of the involvement of AI technologies in various phases of the production process of an enterprise, regardless of its size, structure of the production program and logistics and sales processes. This is attributable to the fact that, as the manufacturing sector is one of the major environmental polluters and active implementers of green innovations, it is necessary to relate them to the efficiency and innovative performance of enterprises. The AI technologies can evaluate quality at the different process levels, optimise processes ([Abd Aziz et al., 2021](#); [Sahu et al., 2021](#)), respond flexibly to changes in the enterprise external conditions, deal with limited resources, cost efficiency and innovation risks. The application of AI technologies in production processes will enable to reveal the other innovative capabilities of green technologies and to adapt them to the new cycle of product development. Eventually, AI will improve the dynamic process coordination and intelligent decision support ([Yang et al., 2022](#)).

Hypothesis 3 aimed at evaluating the association between the adoption of AI technologies in an organisation's business administration processes and eco-innovation in the EU countries. The outcomes of the regression models confirm a significant relationship between these indicators in small, medium and large enterprises. Across all these cases, there was a positive relationship, expressing the fact that a higher eco-innovation output can be associated with a larger number of enterprises using AI technologies in organising business administration processes. The coefficient of determination highlighted that the closest relationship exists in large enterprises, followed by medium-sized enterprises and the smallest value of this indicator was found in small enterprises. The results confirm that even small enterprises successfully adapted AI technologies in the organisation of business administration processes, just as in the case of RQ2. This fact is influenced by the organisational processes in enterprises. For instance, some research studies confirm that the inclusion of AI in individual business

teams can significantly increase productivity (Wilcox and Rosenberg, 2019), but managers must correctly identify not only the types of tasks but also the groups that will benefit most from human–AI collaboration (Bankins *et al.*, 2023). According to Parry *et al.* (2016), the adoption level of AI depends on group characteristics such as size, dynamics and identity.

Hypothesis 4 focused on investigating AI use in selected business processes, and the significance of the relationship between the adoption of AI technologies in the management of enterprises and eco-innovation in EU countries was evaluated. The outcomes of the regression models confirmed a significant relationship between these indicators in medium and large enterprises; however, no significant relationship was confirmed in small enterprises. In all these cases, it was a positive relationship, confirming the fact that a higher level of enterprises using AI technologies in the management of enterprises can be associated with a higher output of eco-innovation. The coefficient of determination acquired low values, except for large enterprises, where it approached the 30% limit. The adoption and use of AI in the management of medium and large enterprises has effected several impulses for improving modern business management processes, as confirmed by many research studies (Kumar *et al.*, 2022; Hansen and Bøgh, 2021). The management concepts of many enterprises across sectors were effectively transformed, operational processes of business enterprises improved, company marketing decision-making processes were optimised, and the directness and intuitiveness of company business also increased (Al-Surmi *et al.*, 2022; Enholm *et al.*, 2022). The adoption of AI in management processes is very extensive, supported by accessibility to internal as well as external data structures. Hence, the importance of AI in enterprises is expected to grow intensively.

The issue of business ethics and sustainability is also related to these processes. It seems that the concept of corporate social responsibility (CSR) will be supplemented by the concept of corporate digital responsibility (CDR) as soon as possible. According to Lobschat *et al.* (2021), the development of the concept of CDR is inevitable, and enterprises must focus on evaluating the impact of digital technologies on business partners in the value chain, data and technology users, among others. According to López Jiménez *et al.* (2021), enterprises will voluntarily commit to a stricter code specific to a particular sector of digital activity. At the same time, this author emphasises the importance of examining the internal processes of corporate self-regulation within digital technologies.

Based on **hypothesis 5**, the interconnection between the adoption of AI technologies in logistics and eco-innovation in EU countries was investigated. The hypothesis of a significant relationship was confirmed within medium and large enterprises but rejected in small firms. In all cases, it was a positive relationship, which expresses that a higher rate of medium and especially large enterprises using AI technologies in logistics is also associated with higher eco-innovation outputs. The stated findings correspond with the results reported by Klumpp (2018), confirming the extensive application possibilities of AI in business logistics systems. Moreover, AI technologies are transforming work tasks in logistics through automation processes and the creation of new job positions (Soumpenioti and Panagopoulos, 2023). Future trends in the adoption of AI in logistics are evident in the integration of AI with robotics, in the integration of AI with blockchain technology, and the implementation of robust cybersecurity measures to protect critical infrastructure and data. The role of AI in logistics will make it possible to achieve higher efficiency and improve decision-making and cost savings (Iyer, 2021). Insufficient use, or lack of interest in the adoption of AI in logistics in small enterprises, is attributable to the lack of clear policies, resistance to the adoption of new technologies and the lack of ethical regulations (Abduljabbar *et al.*, 2019).

Considering **Hypothesis 6**, the interconnectedness between the adoption of AI technologies in marketing or sales with eco-innovation in the EU countries was scrutinised. Based on the results of the analyses, a significant relationship was confirmed only in medium and large enterprises. In all the cases, it was a positive relationship, confirming that a higher rate of medium-sized, especially large enterprises using AI technologies in marketing or sales is also associated with a higher output of eco-innovation. Marketing represents the core business

function in enterprises, which currently has the highest number of AI applications (Chan *et al.*, 2022). A higher level of adoption of AI technologies in marketing and sales processes is also related to the extensive possibilities of using AI in this field. In addition to traditional marketing, AI is also used to manage customer relationships, promotional processes, to optimise advertising spending, increase its quality, improve relevance and location and to effectively communicate with customers. Notably, AI can define the most suitable type of ads for a specific population group (Zulaikha *et al.*, 2020) and evaluate the performance of advertising campaigns and changes in the market. For this reason, insufficient adoption of AI in marketing and sales in small enterprises may stem from insufficient experience with AI applications, knowledge, as well as erroneous beliefs about the sustainability of competitive positions using existing tools.

Hypothesis 7 examines the interconnectedness between the adoption of AI technologies in human resources management or recruiting and eco-innovation in the EU countries. A meaningful relationship was confirmed in medium and large enterprises. In all the cases, a positive relationship confirms the fact that a higher rate of medium-sized, especially large enterprises using AI technologies in human resources management or recruiting is associated with a higher output of eco-innovation. These aforementioned findings are also consistent with the results reported by Johansson and Herranen (2019), who confirm the many benefits obtained from using AI in recruitment processes. The application of AI in recruitment represents new and little-researched processes, but its use is growing. Enterprises should analyse the need to implement AI in this area of HRM and quantify its potential consequences for the company. It is expected that AI can effectively replace existing recruitment systems and make these processes easier for enterprises, save costs, speed up the recruitment process and reach a larger number of candidates (Dickson and Nusair, 2010). Moreover, AI is considered unbiased in these processes, giving an equal chance to all applicants (Upadhyay and Khandelwal, 2018).

Going forward, the governments could face an important task aimed at creating active policies that will strengthen their intelligent development and support the use of AI for the development of green technology innovation. To increase the rate of green technology innovation, it will be necessary to constantly improve the quality of AI development, increase investments in AI technologies in clean and high-tech areas and support the development of active learning and R&D based on intelligent technologies. It will be necessary to accelerate the transformation of machine learning, deep learning and other AI theories into practice (Yin *et al.*, 2023). Not only the growth of investments in R&D, but also a favourable institutional environment supporting investments in AI can support the growth of green technology innovation. For the intensive development of AI and its impact on the growth of green productivity of enterprises and green innovation, continuous regional research and development of AI and innovative technologies for strengthening environmental regulation is essential.

The little explored regional development strategies, support for increasing R&D investments at the regional level and increasing the implementation level of green technology innovation across regions must receive attention. Local governments can play an important role in supporting the economic development of regions, identifying optimal opportunities for increasing investments in intelligent infrastructure, improving the quality of the business environment and developing human resources. Regions can support the creation of a favourable institutional environment and thus facilitate the adaptability of AI and its connection to the growth of green technology innovation. As reported by Yin *et al.* (2023), if the environmental regulation of the institutional environment or R&D investment is insufficient, the coordination of relations between AI and the institutional environment will also be weak. For this reason, it will be necessary to examine the influence of the institutional environment across different regions in relation to the integration mechanisms of AI development. This will make it possible to reveal other determinants of the impact of AI on green technology innovation and adoption possibilities and the barriers to the development of

digitisation at the level of countries and regions. The knowledge of these determinants will enable the implementation of comparative analyses and the creation of conceptual mechanisms that support the creation of effects from connections between AI and green technology innovation.

The outcomes of this study indicate a strong appeal for the creation of an adequate database for a deeper investigation of this issue. The significant limitation of data on the use of AI from the international database Eurostat (2023) has limited our research goals; however, the obtained results will allow us to confront the investigated relationships, conduct comparative analyses and support the creation of optimal policies for small enterprises. As confirmed by Mariani *et al.* (2023), most empirical studies are of a quantitative nature; therefore, the use of qualitative methods is also recommended to capture the adoption and use of AI technologies over time, across different sectors and enterprises with different characteristics. Experiments can also play an important role.

These results confirm the existence of differences in the adoption of AI technologies for eco-innovation outputs across enterprises of different sizes; therefore, it will be important to examine in detail the determinants of the introduction of AI in relation to eco-innovation outputs in different types of enterprises (e.g. private, public). Research studies show that family enterprises encounter significant challenges during the transition to digital transformation (Ceipek *et al.*, 2021); however, this can be supported by adequate policies and mechanisms (Mariani *et al.*, 2023). Enterprise size affects an enterprise's resources and the ability to engage in innovation processes; therefore, it is important to explore the possibility of using digital technologies through external suppliers and partnerships to support innovations leveraging AI technologies, using outsourcing (Mariani and Wamba, 2020).

5.1 Limitations

The key limitations of this study are the fact that the analysis is based on only one year (2021), as these are relatively new technologies and the Eurostat database does not show a longer time series. Another limitation is the problem of endogeneity; thus, these cannot be viewed in terms of causality. Proving causality will be the subject of future research, where the inclusion of a larger number of time periods is also expected. The adoption of AI in businesses is a relatively new phenomenon, where a massive increase in its use is expected to yield several economic-technical benefits and social risks. It is important to assess the relationships of different AI indicators to create a rich base of information that can be useful for creating complex prediction models. Therefore, our future research ambitions will also be directed to the area of quantifying the impact of AI on other indicators of the national economy at the macro and microeconomic levels, related to a sustainable and green economy.

6. Conclusion

During the period of technological development, many enterprises realised the need for intelligent management based on information technologies. Access to big data and technologies used for its processing has significantly influenced management processes and the potential for streamlining work for capturing economic benefits, while increasing risks. At the same time, enterprises have expanded their business scope, as the previous management models could no longer ensure the development of enterprises. The main trend that has emerged is the integration of AI technologies and business management. Digital transformation processes modify the functioning of enterprises according to the principles of the CE, which creates the need to find an application for using AI technologies in achieving eco-innovation outcomes. They can ensure sustainability at the micro and macro levels of economies. Transformation processes are not simple, as countries represent complex systems that are influenced by several economic, social and political factors. Therefore, their adoption, implementation and use require systemic changes that must be institutionally supported.

Governments and the regulatory systems of countries, stabilisation and development mechanisms established by them, will play an important role in these processes. This study confirms the assumption about the existence of significant interconnectedness between several areas of AI use in enterprises and the outcome of eco-innovations. Studies show that technologically advanced countries tend to be more innovative in the ecological field than the less developed ones. The results also show that the relationship between AI use and eco-innovations is the closest in large enterprises. From the perspective of the closeness of the evaluated relationships, medium-sized enterprises follow the lowest rate of the investigated relationships, as demonstrated among small enterprises. Notably, AI technologies in production processes and enterprise management are closely associated with eco-innovations. The cluster analysis visualises the position and comparison of countries in the interconnection of AI use with eco-innovations, while Bulgaria, Poland, Hungary, Romania and Slovakia can be included among countries with the least positive output. The Nordic countries, such as Denmark, Finland and Sweden, were involved among countries with the best outcomes.

The results of this study encourage the implementation of follow-up research focused on under-researched areas, including ecology, innovation and technology. Previous studies have emphasised the importance of environmental policies but did not focus on other policies necessary to drive eco-innovation in enterprises and regional contexts. During the period of digital transformation and the pressure to achieve the goals of sustainable development (SDG17), a systemic coordination of policies is necessary, which would reflect on the ecological, innovative and technological aspects in enterprises and consider the resources, innovative and organisational potential of enterprises. The digitalisation level of enterprises is largely determined by the depth of implementation of the digital technologies.

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Corresponding author

Beata Gavurova can be contacted at: gavurova@utb.cz