Cross-country comparison of the use of artificial intelligence in European companies and its determinants

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Abstract

EU contends that AI offers substantial opportunities to address social challenges such as sustainable development and gender balance. The aim of this paper is identify patterns of behaviour by EU countries in terms of integration of AI into production processes, based on the number of companies that use AI, and distinguishing by sector and company size. Also, it analyses the association between economic development and innovation factors in the EU-27, on the one hand, and the degree of AI use, on the other. Based on a cluster analysis of EU-27 countries' use of AI, Europe can be divided into three groups representing different speeds of digital development. The dominant countries in the field of AI are Denmark and Finland, and those dedicated to ICT also predominate in this regard. Thus, the conclusion drawn is that AI has the potential to contribute to the wealth, productivity and innovation of European countries.

Keywords: Artificial Intelligence, enterprises, innovation, economic growth, employment

JEL: C29; O32; R11

1. Introduction

Artificial Intelligence (AI) is a simulation of human intelligence processes in which machines or computer systems develop theoretical methods and applications (Song et al., 2019; Baruffaldi et al., 2020). Both the concept and early applications of AI emerged in the 1950s (Turing, 1950); however, the integration of AI into economic and social spheres

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is a recent development. By its nature, AI technology pervades all industrial sectors, digital services and social life (Craglia et al., 2018). Nevertheless, there are concerns that advances in AI could affect the labour market, companies and industries, displacing workers, transforming occupational jurisdictions, and altering strategy and competitiveness (Felten et al., 2021).

At a global level, the United States leads the world in terms of private investment in AI, with a total of 47.4 billion dollars in 2022, an amount approximately three-and-a-half times that of China (Maslej et al., 2023). Compared to China and North America, Europe lags somewhat in the development of AI solutions, both in the public and private sectors (Fernandez et al., 2022). However, the European Union (EU) is taking action to enhance the use of AI and establish a normative regulatory framework in accordance with European values and principles (Gamero, 2021).

Against this backdrop, the aim of this paper is twofold. The first is to identify patterns of behaviour by EU member states in terms of the integration of AI into production processes, based on the number of companies that use AI, and distinguishing by sector (Manufacturing, Construction, Wholesale and retail trade, Transportation and storage, Accommodation and food services, Information and communication, and Administrative and support service) and company size (small, medium and big). To this end, cluster analysis is applied, identifying homogeneous groups of countries in terms of their incorporation of AI in 2021. The second aim is to analyse the association between economic development and innovation factors in the EU-27, on the one hand, and the degree of AI use, on the other. The association is assessed by calculating the chi-square statistic from the contingency tables created. To achieve the aforementioned aims, two research questions are posed, providing structure to the analysis and allowing an assessment of the results.

Q1: Is there a divide between EU countries in terms of their companies' use of AI?

Q2: What economic and innovation factors are associated with a level of AI use in the business world?

The answer to these research questions reveals the situation in Europe in terms of companies' incorporation of AI, where the degree of divergence among countries is estimated by determining how many homogeneous groups of nations can be identified and the distance between them. An understanding of this situation can help European organizations to plan their investment strategies. The paper presents an original new approach in relation to the integration of AI in European companies. The first original element is the selection of the set of variables that capture companies' engagement with AI, focusing on sector and company size, which have not previously been jointly addressed. Furthermore, the analysis of the association between economic and innovation factors and the level of AI integration in companies represents a novel approach that can help guide economic policies aimed at driving the development of new technologies.

The rest of the paper is structured as follows. Section 2 presents a literature review focused on the integration of AI in different economic sectors and the EU's commitment to technological development. Section 3 explains the methods and the sample used in the empirical analysis. Section 4 details and discusses the main results of the research. Finally, section 5 presents the main conclusions and limitations of the paper.

2. Literature review

2.1 Artificial intelligence at the sector level

AI is being incorporated into the production and service processes of various economic activities. Companies' AI capabilities include robotic process automation, text understanding, virtual agents, service operations optimization, the creation of new products, customer segmentation, customer service analytics and product enhancement, among others (Maslej et al., 2023).

Focusing on the primary sector, Ayed and Hanana (2021) and Sharma et al. (2022) emphasize the importance of AI and machine learning as part of a multidisciplinary predictive approach to improve the food and agricultural sector and achieve the increase in agricultural production needed to feed the ever-growing global population. Along the same lines, Javaid et al. (2023) show that AI helps farmers to select the optimal time to plant their seeds. Intelligent equipment calculates the spacing between seeds and the maximum planting depth, as well as giving farmers information about the health of their crops and the nutrients needed to enhance yield quality and quantity.

Within the activities of the secondary sector, the competitiveness of the manufacturing industry can be improved by the application of AI in countries with high cost structures. Factories will become agile production facilities that can be easily restructured to meet different needs, and places where people and automation work together flexibly (Rizvi et al., 2021). According to Wang et al. (2023a), AI positively influences the productivity of manufacturing companies, but its impact varies depending on geographical location, industrial characteristics, ownership and stages of the product life cycle.

Finally, in the tertiary sector, a growing trend of AI use is observed in different areas. Johnson et al. (2022) note how automation is more common in public administration, information and communication technology (ICT) and software. In addition, they conclude that AI leads to an increase in human labour rather than replacing it. In this vein, van Noordt and Misuraca (2022), focusing on the EU, show that AI is primarily applied to improve the provision of public services and internal management; in only a limited number of cases does it directly or indirectly support political decision-making. In the ICT sector, Fatima et al. (2020) conclude that new technologies generate significant savings in terms of costs, time and processes, with high-growth areas being the cloud, networks and system security. The educational sector has also been engaged with AI use. Popenici and Kerr (2017) investigate the educational implications of AI for the way students learn and how institutions teach and evolve. In relation to the hospitality industry, research shows how AI models are applied to large volumes of data to detect large scale industry trends and customer opinions, offering recommendations on places to visit and allowing hotels and vacation rental owners to use automated pricing solutions based on supply and demand (Nam et al., 2021; Limna, 2022).

2.2 Artificial intelligence in the EU

The EU has promoted and regulated AI innovation in recent years, such that companies are starting to voluntarily disclose information about their AI initiatives (Bonsón et al., 2021). According to Woszczyna and Mania (2023), the policies on AI that are currently in effect in EU countries show significant differences in their approach to managing AI, meaning its use varies between companies of different EU states. Since 2015, the EU has been working to incentivize the development of AI; that said, the focus has not been on AI exclusively but as part of a digitalization environment where aspects such as improving cybersecurity and the European Cloud Initiative are also important (Carriço, 2018).

Some years on, the EU now contends that AI offers substantial opportunities to address social challenges such as sustainable development, gender balance, improved health, climate change and the circular use of resources (European Commission, 2018). Specifically, the EU member states signed the Declaration of Cooperation on Artificial Intelligence, where they agreed to work together on the most important issues raised by AI, from ensuring Europe's competitiveness in the research and deployment of AI, to dealing with social, economic, ethical and legal questions (Craglia et al., 2018).

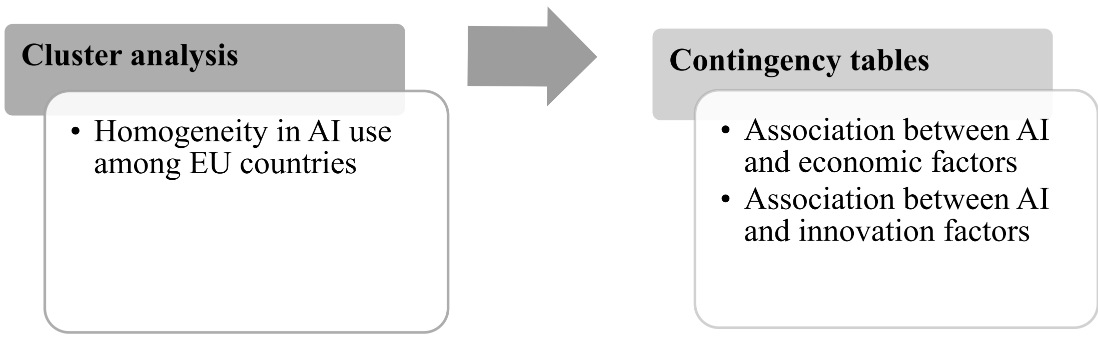
Subsequently, in 2019, the European Commission created as part of its AI strategy the High-Level Expert Group on Artificial Intelligence, a group of independent experts tasked with drawing up Ethical Guidelines for Trustworthy AI (European Commission, 2019). Thus, in 2020, the Commission published a White Paper on AI (European Commission, 2020a), describing AI as a "collection of technologies that combine data, algorithms and computing power", and concluding that Europe could combine its technological and industrial strengths with a high-quality digital infrastructure and a regulatory framework based on its fundamental values to become a global leader in innovation in the data economy and its applications, as set out in the European data strategy. Straus (2020) notes that the white paper is intended to establish policy options on how to achieve the dual objective of promoting the adoption of AI and addressing the risks associated with certain uses of this new technology.

More recently, in 2021, the EU launched the Digital Europe Programme aimed at financially supporting the digital transformation of European societies and economies. It focuses on five key areas: supercomputing, AI, cybersecurity, advanced digital skills and the use of digital technologies in the economy (European Commission, 2020b). In the near future, it will be approved The AI Act, the first comprehensive regulation on AI by a major regulator anywhere. The Act assigns applications of AI to three risk categories. First, applications and systems that create an unacceptable risk, such as government-run social scoring of the type used in China, are banned. Second, high-risk applications, such as a CV-scanning tool that ranks job applicants, are subject to specific legal requirements. Lastly, applications not explicitly banned or listed as high-risk are largely left unregulated (https://artificialintelligenceact.eu/).

3. Material and methods

This study—the aim of which is to evaluate homogeneous patterns of behaviour regarding the integration of AI in companies in the 27 EU member states, as well as the economic and innovation factors associated with the level of engagement with AI— has been carried out using information from Eurostat and employing cluster analysis and contingency tables (Fig 1).

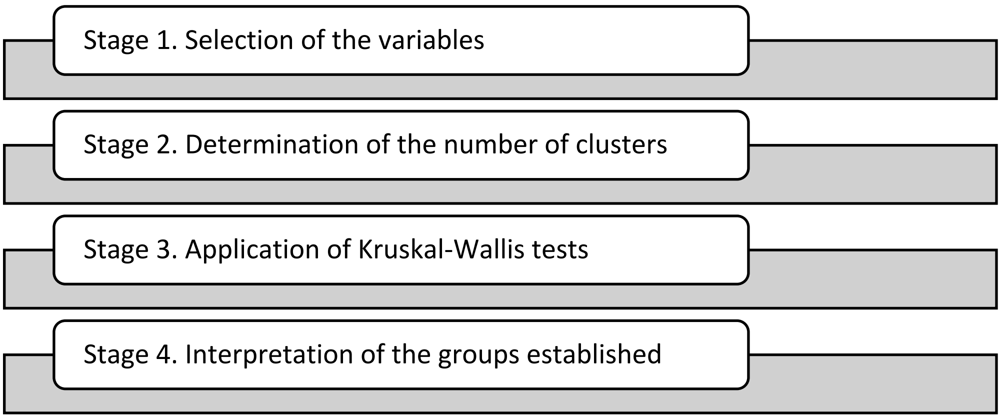
Fig. 1. Research design



3.1 Methods

Cluster analysis is a multivariate method aimed at dividing the heterogeneous data in a sample into homogeneous groups with identifiable patterns of behaviour (Everitt et al., 2011; Backhaus et al., 2023). It is a technique that has been used successfully in a variety of contexts, such as climate change (Puertas and Marti, 2021), food safety (Marti et al., 2021) and economic growth (Brida et al., 2020). Recently, various papers focusing on the digital sphere have applied cluster analysis (Wang et al., 2023b; Conti et al., 2023; Pernici and Stancu, 2023; Pinto et al., 2023; Călinescu, 2023, Buck et al, 2023). The cluster analysis is carried out in four sequential stages (Fig. 2).

Fig. 2. Stages of the cluster analysis



In this paper, following the stages of the hierarchical cluster analysis procedure (Fig. 2), stage 1 is based on the variables that represent the number of companies using AI in EU member states, differentiating by sector and by size. Then, in stage 2, the number of clusters is determined by applying Ward's hierarchical agglomerative clustering method based on the squared Euclidean distance as a measure of similarity. According to Kuiper and Fisher (1975), this classification technique combines different elements, seeking to minimize the within-group variance. From these results, a dendrogram can be created, indicating the ideal number of clusters.

Next, in stage 3, the Kruskal-Wallis test is applied to confirm the adequacy of the established division. This test is used to check that the mean of each of the groups is statistically different from the rest. Finally, in stage 4, based on the characteristics of each homogeneous group of countries, a pattern of behaviour is established to identify the level of AI use, thus enabling the design of appropriate guidelines to ensure continuing progress in the new digital era.

In line with the research aims, the second part of this study involves producing contingency tables to analyse the association between the degree of AI use (according to membership in each cluster) and the economic and innovation indicators of European countries. This methodology has been used in different contexts, such as in the areas of mobile applications (Benbunan-Fich and Benbunan, 2007), consultative democracy (Bogliacino et al., 2018), sustainable development (Puertas and Marti, 2023), and even radiology (Kuo et al., 2022; Cohen et al., 2023).

The general structure is illustrated in Table 1, where the rows and columns represent the number of countries whose indicator is at the same level, constituting the observed frequency. The scores have been transformed into qualitative variables related to belonging to a cluster (for the AI variable) or to a quartile (in relation to economic or innovation variables).

Table 1. General structure of contingency tables of observed frequencies

VARIABLE "Y"

	Criterion *i*	CL 1	CL 2	Total
VARIABL	Q1	$n_{1,1}$	$n_{1,2}$	$n_{1,\bullet}$
	Q2	$n_{2,1}$	$n_{2,2}$	$n_{2,\bullet}$

Q3	$n_{3,1}$	$n_{3,2}$	$n_{3,\bullet}$
Q4	$n_{4,1}$	$N_{4,2}$	$n_{4,\bullet}$
Total	$n_{\bullet,1}$	$n_{\bullet,2}$	$n_{5,\bullet}$

Based on the data in Table 1, the expected frequencies are calculated using the following expression:

$$E_{ij} = \frac{n_i.n._j}{N} \quad (1)$$

Where, N is the total number of observations in the table, $n_{i,\bullet}$ is the number of observations in row i, and $n_{\bullet,j}$ is the number of observations in column j.

Both the observed and expected frequencies are necessary to perform the chi-square test test showing whether the variables considered in the study are independent or not. The result of the χ^2 test confirms whether the levels of a qualitative variable influence those of another variable. The χ^2 test is defined by the following expression:

$$\chi^2 = \frac{\sum_{i=1}^{h}\sum_{j=1}^{k}(n_{ij} - E_{ij})^2}{E_{ij}} \quad (2)$$

Where, n_{ij} is the observed frequency, and E_{ij} is the expected frequency. The null hypothesis is that of independence between factors. The alternative hypothesis is that of dependence between factors.

3.2 Material

The homogeneous groups of EU countries in terms of their level of engagement with AI have been identified based on information published by Eurostat (https://ec.europa.eu/eurostat/data/database). The cluster analysis applied focuses on two elements: first, a classification of companies by sector, where the variables represent the percentage of companies that use AI at country level in 2021, including in the analysis companies that have at least 10 employees, and dividing them into the following sectors: 1. Manufacturing, 2. Construction, 3. Wholesale and retail trade, 4. Transportation and storage, 5. Accommodation and food services, 6. Information and communication and 7. Administrative and support service. Second, companies are classified by their size: big (250 employees or more), medium (from 50 to 249 employees) and small (from 10 to 49 employees). Thus, the data sample is composed of two matrices with a composition of 27 EU countries (rows) and 7 columns according to the sectoral classification, while there are 3 columns in the size classification. These two cluster analyses make it possible to identify the degree of fragmentation in the EU in terms of companies' AI-related behaviour.

The second part of this research involves the use of contingency tables to assess the association between the clusters identified and the economic and innovation conditions in European countries. Since this methodology requires the use of categorical variables, the economic and innovation variables must be transformed based on membership of the corresponding quartiles (Table 2).

Table 2. Economic and innovation variables classified in quartiles

	quartile 1	quartile 2	quartile 3	quartile 4
Patents (1)	22-56	69-203	290-2309	2480-25891
GDP pc (2)	10330-17850	18440-24800	25500-43480	45280-112880
Employment (3)	62.6-73.2	74.1-75.4	75.6-78.8	79.1-81.7
Productivity (4)	87.65-108.11	109.52-115.08	116.98-124.66	124.76-143.78

Note: The units of measurement of each variable are (1) Number; (2) Euros; (3) % of population; (4) Index 2015=100

Patents, GDP pc, employment and productivity come from Eurostat, using 2021 values as it is the year under analysis. The variables are specific for each of the 27 EU members, and their statistics are explained in Table 3.

Table 3. Main statistics

	Variable	Unit of measurement	Mean	SD	Max	Min
Artificial Intelligence	Manufacturing	% of companies	8.23	5.93	27.30	1.20
	Construction	% of companies	4.14	3.53	11.30	0.00
	Wholesale and retail trade	% of companies	6.78	5.03	21.30	0.60
	Transport and storage	% of companies	6.71	4.83	21.30	0.30
	Accommodation	% of companies	3.65	3.88	16.70	0.00
	Information (ICT)	% of companies	25.16	10.50	54.80	8.80
	Administrative	% of companies	7.99	5.21	21.40	1.80
	Small (1)	% of companies	6.51	4.60	19.70	1.10
	Medium (2)	% of companies	12.89	8.10	37.30	1.90
	Big (3)	% of companies	27.56	13.47	66.20	7.10

Economic and innovation factors	Patents	Number	2511.9	5315.8	25891	22
	GDP pc	Euro per capita	34,034	23,465	112,880	10,330
	Employment (4)	% of population	74.6	5.1	81.7	62.6
	Productivity (5)	Index 2015=100	116.5	12.7	143.7	87.6

Notes: (1) From 10 to 49 employees; (2) From 50 to 249 employees; (3) 250 employees or more; (4) Population aged 20 to 64; (5) Nominal unit labour cost based on hours worked

The descriptive statistics relating to the percentage of companies using AI indicate that companies in the ICT sector are the most engaged with such practices, registering a mean value of 25.16%. However, this is also the branch of activity showing the greatest dispersion; in other words, the highest degree of inequality, reaching a maximum value of 54.8% of companies from Denmark compared to a minimum value of 8.8% registered by Romanian companies. Conversely, the hospitality industry has the lowest mean percentage of companies that use AI (only 3.65%); its dispersion is also very low, indicating a certain degree of homogeneity among EU member states. Regarding the size of companies, there are on average more big companies that use AI (27.5%), followed by medium-sized (12.9%) and small (6.5%), with this being a factor proportional to use. Bonsón et al. (2021) conclude that larger companies, those belonging to the technology and telecommunications sectors, and those from Southern European countries are more likely to disclose information about AI activity.

The statistics show that Germany leads the way in innovation in Europe, recording the maximum value of 25,891 patents in 2021, while economic conditions are noteworthy in Luxembourg and the Netherlands, which record the highest GDP pc (112,880 euros) and employment (81.7% of the population), respectively. Finally, Romania is the leading European country in terms of productivity growth, achieving a value 43.7% higher than the value in 2015, while Ireland records a drop of 12.4%.

4. Results and discussion

The EU is trying to position Europe as a global centre of excellence in AI. The unstoppable growth of new technologies makes it important to understand the inequalities or similarities among different groups of countries. In this context, the present study provides answers to two research questions:

Q1: Is there a divide between EU countries in terms of their companies' use of AI?

The cluster analysis carried out for the 27 EU member states has focused on two elements: the classification of companies by sector, and by size. The application of Ward's hierarchical agglomerative clustering method has yielded two dendrograms, one for sector variables and the other for company size variables (Figures 1A and 2A in the appendix). Three groups of countries have been identified in both cases.

Table 4. Clustering of countries according to the applied criteria

	Criterion: Companies classified by sector	Criterion: Companies classified by size
Cluster 1: Worst	Bulgaria, Cyprus, Czechia, Estonia, France, Greece, Hungary, Italy, Latvia, Lithuania, Poland, Romania, and Slovakia	Bulgaria, Croatia, Cyprus, Czechia, Estonia, Greece, Hungary, Italy, Latvia, Lithuania, Malta, Poland, Romania, and Slovakia
Cluster 2: Intermediate	Austria, Belgium, Croatia, Finland, Germany, Ireland, Luxembourg, Malta, Netherlands, Portugal, Slovenia, Spain, and Sweden	Austria, Belgium, France, Germany, Ireland, Luxembourg, Netherlands, Portugal, Slovenia Spain and Sweden
Cluster 3: Best	Denmark	Denmark and Finland

In summary, the percentage of companies that use AI reveals a divide in Europe when it comes to the integration of these new technologies. Three groups of countries have been identified based on the AI use of companies classified by sector and by size. The two criteria applied yield similar groups, which further supports the divide detected, and provides an affirmative answer to research question Q1 (Table 4). The application of the Kruskal-Wallis test statistically demonstrates that the groups are significantly different from each other in all cases (p-value<0.05), while the countries belonging to the same group have characteristics in common (Table 5).

Table 5. Results of the cluster analysis and Kruskal-Wallis test

	% of companies using AI classified by sector						
	Manufact[1]	Construc[2]	Trade	Transp[3]	Accomm[4]	ICT[5]	Admin[6]
Total mean	8.23	4.14	6.78	6.71	3.65	25.16	7.99
C1 mean	3.85	1.7	2.94	3.55	1.25	16.64	4.45
C2 mean	11.14	6.22	9.51	8.74	5.39	31.39	10.68
C3 mean	27.30	8.90	21.30	21.30	12.20	54.80	19.00
			Kruskal-Wallis Test				
chi-sq	18.7	10.6	1.3	12.7	13.4	18.7	14.6
p-value	.000	.001	.000	.000	.000	.000	.000
	% of companies using AI classified by size						
	Small	Medium	Big				

Total mean	6.51	12.89	27.56
C1 mean	3.5	7.2	17.2
C2 mean	8.7	16.7	35.1
C3 mean	16.1	32.0	58.7
			Kruskal-Wallis Test
chi-sq	15.6	17.9	20.6
p-value	.000	.000	.000

Note: 1. Manufacturing; 2. Construction; 3. Transportation and storage; 4. Accommodation and food services; 5. Information and communication; 6. Administrative and support service.

Cluster 1 is predominantly made up of companies from Eastern Europe, where they have a lot of room for improvement in terms of technology, partly due to the lack of human resources trained in the use of AI. In this group of countries, the companies using AI that are from the ICT sector (16.6%) predominate over those from the Accommodation and food service sector, where only 1.25% of companies use AI. With respect to size, an important difference is detected between big companies, which represent 17.2% of AI users, compared to small companies with 3.5%. In this context, Brodny and Tutak (2021b) report that innovation activity is still limited in Eastern Europe, and spending on research and development relative to GDP is two times lower than the EU average, making it difficult to achieve the digital progress seen in other areas of Europe.

Cluster 2 is made up of countries with an average level of companies that use AI. These are companies from all over Europe: Spain and Portugal (south), Belgium, the Netherlands, Germany, Austria, Slovenia, Croatia (central), Sweden and Finland (north). As in cluster 1, they are mostly companies that belong to the ICT sector (31.4%) and are large in size (35.1%); however, the percentages are above the mean in all sectors and sizes. These results are in line with those of Igna and Venturini (2023), who show that for European companies, innovation in AI yields positive returns in the area of network and communication technology, high-speed computing, data analytics and imaging.

Cluster 3 is classified as “the best", as it is made up of countries with a high percentage of companies that use AI, according to both the sector criterion and the size criterion. It is a group composed exclusively of Danish companies in the case of the sector classification, and by companies from Denmark and Finland when classifying by size. The exclusive nature of this group means the behaviour can be taken as a model to follow for the rest of the continent. These results coincide with those of Brodny and Tutak (2021a) indicating that companies in Finland, Denmark, the Netherlands, Belgium and Sweden show a high level of digitalization compared to the rest of Europe. According to Jørgensen

(2023), the public administration in Denmark relies heavily on the processing of huge quantities of data about individuals and is increasingly making use of predictive analytics to identify specific areas of intervention, such as fraud or vulnerability, as part of its decision-making processes.

Q2: What economic and innovation factors are associated with a level of AI use in the business world?

The literature supports the idea that AI can be used to analyse and predict economic factors (Batarseh et al., 2020; Mero et al., 2020; Gries and Naudé, 2022); however, this paper raises the possibility of an association between economic indicators and the use of AI. The variables that determine a country's economic situation (GDPpc, employment and productivity) and its innovation activity (patents) have been divided into quartiles (Table 2) and companies' degree of engagement with AI is defined by membership in one of the clusters. Table 6 shows the statistics for the contingency tables produced (Tables 1A and 2A in the appendix), identifying the variables between which there is dependency (chi-sq, p-value < 0.05) and the direction of dependency (gamma < 0.05).

Table 6. Statistics for the contingency tables

	% of companies using AI classified by sector			
Variable X-Variable Y	chi-sq	p-value	gamma	p-value
Artificial intelligence-Patents	8.190	0.042	0.557	0.022
Artificial intelligence-GDPpc	10.381	0.016	0.818	0.000
Artificial intelligence-Employment	1.510	0.680	0.344	0.216
Artificial intelligence-Productivity	12.286	0.006	0.448	0.084
	% of companies using AI classified by size			
Artificial intelligence-Patents	14.878	0.021	0.839	0.000
Artificial intelligence-GDPpc	14.105	0.028	0.837	0.000
Artificial intelligence-Employment	6.158	0.406	0.234	0.314
Artificial intelligence-Productivity	16.631	0.011	0.647	0.040

In this research, the chi-square test confirms that a good economic and innovation situation is linked to the use of AI, regardless of whether the analysis is based on sector or company size classification. In short, AI has the potential to contribute to the wealth and competitiveness of European countries, thus requiring responsible governance and business policies (Fajardo de Andara, 2019; Irion and Williams, 2020).

The positive and significant association between patents and the use of AI demonstrated by the chi-square statistic is in line with findings of other studies (Damioli et al., 2021; Yang, 2022; Rammer et al., 2022; Czarnitzki et al., 2023). Furthermore, this study confirms the significant and positive association between business productivity and the use of AI, in accordance with the results of Graetz and Michaels (2018), who concluded that robots have been able to increase the average industrial productivity growth of 17 countries. More precisely, Gao (2023), using a sample of manufacturing companies, concludes that a 1% increase in AI penetration can lead to a 14.2% increase in total factor productivity.

However, employment is the only indicator that is not associated with better AI engagement. This finding aligns with the conclusions of Craglia et al. (2018), indicating that the literature is not conclusive on the effects of robotization on employment; contradictory conclusions emerge depending on the research approach. For example, Chiacchio et al. (2018) found that robots may directly displace workers from performing specific tasks, while at the same time increasing the demand for labour thanks to the efficiency they bring to industrial production. For their part, Aghion et al. (2020) show a positive impact of AI use on employment levels. In the same vein, Albanesi et al. (2023) confirm that employment in Europe has increased more in the occupations that are most exposed to AI, further noting that this is particularly true for occupations with a relatively greater proportion of younger and more highly qualified workers.

5. Conclusions

New technologies, including AI, are erupting into the economies of developed countries at an ever greater rate. Therefore, research in this area seeks to provide a better understanding of the situation to be able to target resources where they are most needed. The economic impact of AI is still unknown due to the difficulties in measuring the advances in this technological field and the time it takes for these innovations to yield benefits. However, recent literature has been reaching conclusions about the influence of AI on factors such as productivity, employment and innovation. Against this backdrop, the present study continues a line of research in order to identify homogeneous behaviour by EU member states in terms of the integration of AI into production processes, and to analyse the association between AI and economic and innovation factors.

Based on a cluster analysis of EU-27 countries' use of AI, Europe can be divided into three groups representing different speeds of digital development. The dominant countries in the field of AI are Denmark and Finland, where more than 50% of large companies use AI in their production processes, and those dedicated to ICT also predominate in this regard. At the other extreme are the more technologically backward nations in Eastern Europe, with deficiencies in investment and human resource training that prevent them from advancing at the same pace as the rest of Europe.

Thus, the conclusion drawn is that AI has the potential to contribute to the wealth, productivity and innovation of European countries. However, AI does not show a clear association with employment. This may be because as long as humans have creative capacity it will be difficult for technology to be a perfect substitute for human labour. Creativity encompasses intentions, emotions, aesthetic judgements, values, personal conscience and morality—things that cannot be mastered by an algorithm, the basis of an AI system. In summary, AI is a valuable growth factor in which European economies must invest to reach the levels of the United States and China. One limitation of this research is that the data on companies using AI come from a single year. Therefore, statistics that provide information for more years and more sectors would make it possible to identify the reach of AI and its economic impact on all EU countries.

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Appendix

Figure 1A. Dendrogram of countries' companies classified by sector

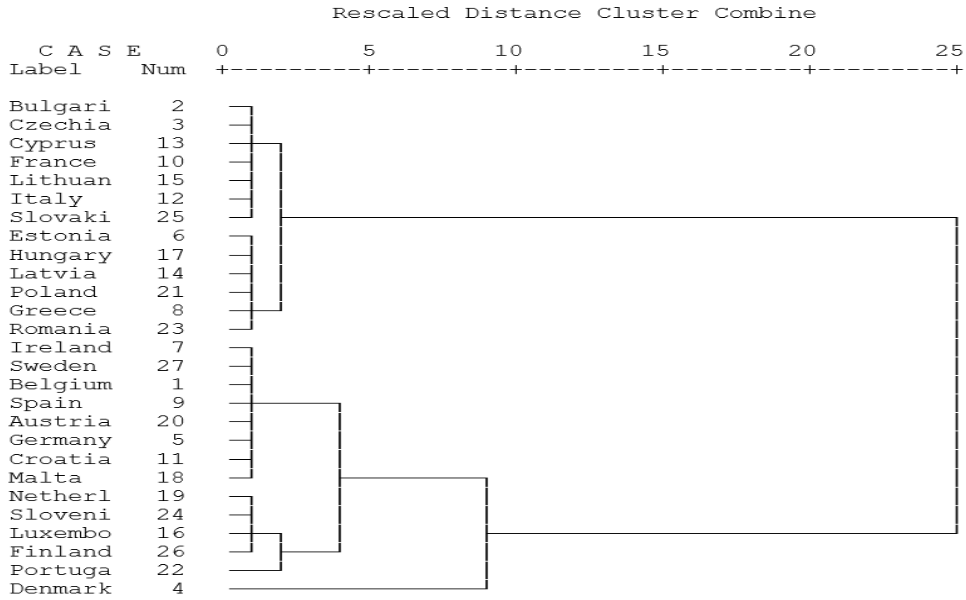

Figure 2A. Dendrogram of countries' companies classified by size

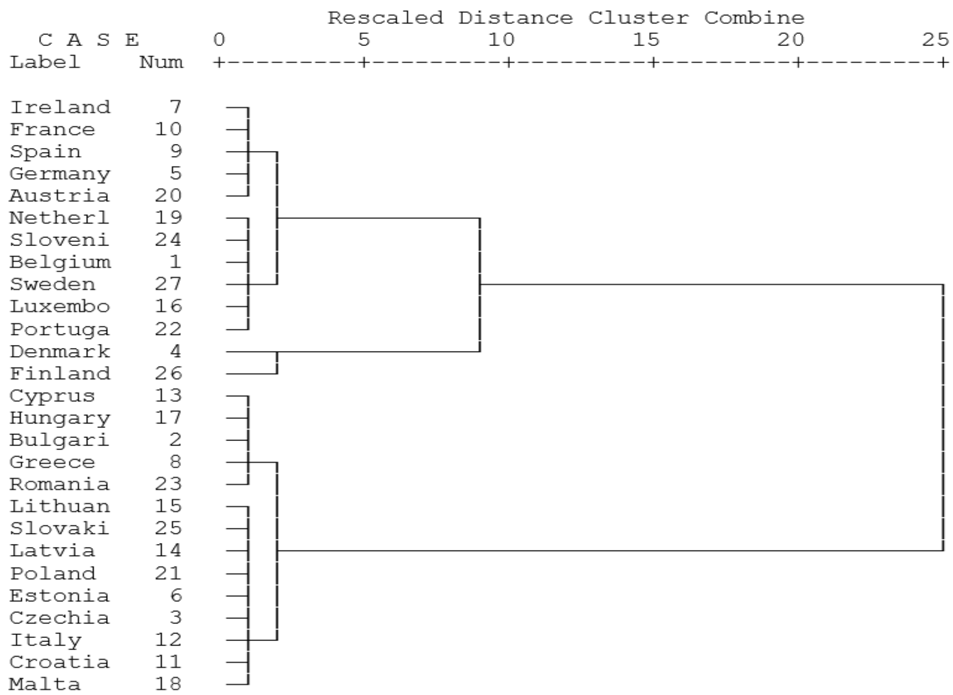

Table 1A. Contingency tables between AI and economic and innovation factors of companies classified by sector

		ARTIFICIAL INTELLIGENCE						ARTIFICIAL INTELLIGENCE			
		C1	C2	C3	Total			C1	C2	C3	Total
PATENTS	Quartile 1	5	2	0	7	GDP PC	Quartile 1	6	1	0	7
	Quartile 2	5	2	0	7		Quartile 2	4	3	0	7
	Quartile 3	1	6	0	7		Quartile 3	3	4	0	7
	Quartile 4	2	3	1	6		Quartile 4	0	5	1	6
	Total	13	13	1	27		Total	13	13	1	27
		ARTIFICIAL INTELLIGENCE						ARTIFICIAL INTELLIGENCE			
		C1	C2	C3	Total			C1	C2	C3	Total
EMPLOYMENT	Quartile 1	5	3	0	8	PRODUCTIVITY	Quartile 1	4	2	1	7
	Quartile 2	3	3	0	6		Quartile 2	0	7	0	7
	Quartile 3	3	4	1	8		Quartile 3	3	4	0	7
	Quartile 4	2	3	0	5		Quartile 4	6	0	0	6
	Total	13	13	1	27		Total	13	13	1	27

Table 2A. Contingency tables between AI and economic and innovation factors of companies classified by size

		ARTIFICIAL INTELLIGENCE						ARTIFICIAL INTELLIGENCE			
		C1	C2	C3	Total			C1	C2	C3	Total
PATENTS	Quartile 1	7	0	0	7	GDP PC	Quartile 1	7	0	0	7
	Quartile 2	5	2	0	7		Quartile 2	4	3	0	7
	Quartile 3	1	5	1	7		Quartile 3	3	3	1	7
	Quartile 4	1	4	1	6		Quartile 4	0	5	1	6
	Total	14	11	2	27		Total	14	11	2	27
		ARTIFICIAL INTELLIGENCE						ARTIFICIAL INTELLIGENCE			
		C1	C2	C3	Total			C1	C2	C3	Total
EMPLOYMENT	Quartile 1	5	3	0	8	PRODUCTIVITY	Quartile 1	3	2	2	7
	Quartile 2	3	3	0	6		Quartile 2	1	6	0	7
	Quartile 3	4	2	2	8		Quartile 3	4	3	0	7
	Quartile 4	2	3	0	5		Quartile 4	6	0	0	6
	Total	14	11	2	27		Total	14	11	2	27