STUDIES

# Statistics on the use of AI technologies in the member states of the EU

**Gergely Lülök**
Budapest University of Technology and Economics, Department of Management and Business Economics, Hungary
Email: lulok.gergely@edu.bme.hu

**Imre Dobos**
Budapest University of Technology and Economics, Department of Economics, Hungary
Email: dobos.imre@gtk.bme.hu

**Zoltán Sebestyén**
Budapest University of Technology and Economics, Department of Management and Business Economics, Hungary
Email: sebestyen.zoltan@gtk.bme.hu

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This study provides a comprehensive statistical analysis of the uptake and application of artificial intelligence (AI) technologies in the European Union (EU) member states up to 2023. The research draws on data from 150,400 companies to examine the relationship between different AI technologies such as machine learning, process automation and text mining. Using correlation, factor and principal component analysis, the study explores the extent and effectiveness of the integration of technologies, providing a new scientific perspective on the industrial application and strategy of AI-based innovations. The analysis has revealed that countries with higher levels of digital skills and advanced technological infrastructure, such as Denmark and Finland, exhibit significantly higher AI adoption rates. Furthermore, the results highlight how closely certain technologies, such as machine learning and robotic process automation, are related. The results offer significant contributions to facilitate a more effective application of AI technologies in the European industrial environment and provide guidance for future development strategies.

## Introduction

This study provides a comprehensive statistical analysis of the use of artificial intelligence (AI) technologies in the European Union member states up to the year 2023, based on data from 150,400 companies and examines correlations between AI technologies such as machine learning, robotic process automation, text mining and speech recognition. Statistical methods, including correlation and principal component analysis, are used to identify the relationships between technologies and their industry characteristics. The results show that the diffusion of AI technologies is closely correlated with countries' economic development and level of digitalisation. The research reveals differences in technological development between different regions of the EU and provides important guidelines for promoting the integration of AI technologies, especially in Central and Eastern European countries.

The results show that some technologies – such as machine learning and robotic process automation – are closely linked, which can lead to significant efficiency gains, while others are less so. The paper pays particular attention to the correlation matrix and its determinant, which prepares the ground for factor analysis and highlights multicollinearity between variables.

The factor structures defined using Kaiser–Meyer–Olkin (KMO) and Bartlett's test allow a robust and valid analysis of the relationships between different technologies. The resulting factors can help researchers and policymakers to design and optimise strategies for the successful integration of AI technologies in industry and services.

Our research contributes to the growing body of literature examining AI adoption and digital transformation across European countries. While previous studies have explored various aspects of technological integration, such as the economic and social impacts of digitalisation, they often lack a comprehensive framework that combines economic capacity, technological readiness, and regional disparities. In this study, we address this gap by employing advanced statistical methods to uncover the underlying patterns and drivers of AI adoption, providing a holistic perspective that integrates multiple dimensions of analysis.

Overall, the paper not only explores the current diffusion and applications of AI technologies, but also offers a deeper scientific understanding of the interrelationships between the technologies and their impacts in economic and technological contexts. The results of the research can contribute to the design of future AI-based innovation and development strategies, especially in the European industrial context.

## Literature review

Artificial intelligence and related digital technologies, such as big data and robotics, are fundamentally transforming economies and societies around the world. In the

European Union, these technologies play a key role in modernising industry, increasing competitiveness and driving economic growth. However, the use of AI varies significantly between member states, influenced by a number of factors, including the economic development of each country, its level of digitalisation, its investment in research and development (R&D), and national policies and regulations. The aim of this chapter is to provide a comprehensive picture of the uptake of AI technologies in the EU, the level of digitalisation and robotization, and the resulting economic and social impacts. It draws on the relevant academic literature to present the role of AI and related technologies in different industries and regions, highlighting the logical links, similarities and differences. The synthesis helps to understand how the use of information and communication technologies (ICT) can contribute to the EU's economic and social goals and what challenges need to be addressed to reduce the digital divide.

## State, practice and trends of AI in the European Union

The differences in the use of artificial intelligence and digital technology between European countries have been analysed in detail in several studies. Zoumpekas et al. (2021) compared Greece's innovation performance with the EU average. The study found that Greece outperforms the EU average in indicators such as digital public service quality and the development of human capital through digital skills education while lagging behind other EU countries in terms of technological infrastructure. Juhász et al. (2022) looked at the digital competence development of EU countries and found that Nordic countries such as Denmark and Sweden are at the forefront in the adoption of Industry 4.0 and AI-based systems. Similarly, Duch-Brown (2022) highlighted Germany's dominance in the EU robotics market. Despite this dominance, Germany's market share is declining, while Denmark and Spain show increasing market shares.

Chan–Meunier-Aitsahalia (2020) point to differences in digital skills between EU countries, with Luxembourg and the Netherlands leading the way, while Bulgaria and Romania lag behind, particularly in the use of AI-based technologies. According to Daroń–Górska (2023), 23.9% of Danish companies use AI, well above the EU average, while in Romania the figure is only 1%. This is supported by Brodny–Tutak (2022), who highlight the high levels of AI adoption in Finland and Denmark, compared to Bulgaria, where AI use is barely 3%. Research by Vasilescu et al. (2020) shows that digital skills vary widely across countries, with 97% of the Swedish population having adequate digital skills, compared to only 57% in Hungary.

Pejić Bach et al. (2020) studied the use of big data in Europe, where 33.5% of large companies use these tools, compared to only 10.57% of small companies. Malinowski (2021) concludes that science and technology (S&T) development and living standards are closely related, especially in countries such as Lithuania and Slovenia, where high technology levels lead to increased living standards.

Pripoaie et al. (2024), examining the AI development in Romania, found that the country is making progress in this area, but lags behind more developed European countries. This finding is in line with the results of Botlíková–Botlík (2020), who found that Germany, France and the UK lead the EU in artificial intelligence R&D expenditure, while less developed regions have not yet reached similar levels.

Brodny–Tutak (2021) analysed in detail the level of AI and robotization in EU member states and found that 16% of businesses in Finland use AI, compared to only 3% in Bulgaria. In Denmark, the AI adoption rate is particularly high, reaching 24%, while in Germany it is 11%. These disparities reflect differences in the use of AI technologies across EU countries, directly affecting economic growth and competitiveness. Building on these results, Brodny–Tutak (2022) further investigate the use of AI, distinguishing between countries at the "expert" and "novice" levels. In the "expert" category, such as Denmark and Finland, the use of AI is 24% and 15.8%, while "novice" countries, such as Romania and Bulgaria, show rates of only 1.4% and 3.3%, respectively. The findings of the two studies show a strong correlation, as both analyses highlight that higher AI adoption rates are associated with more competitive, innovative economies. In contrast, lower AI use hinders economic development in less developed countries.

The research reviewed shows that there are significant differences in the level of AI and digitalisation between European countries. More developed countries such as Denmark, Finland and Germany excel in the use of artificial intelligence and digital technologies, while Eastern European regions such as Romania and Bulgaria lag behind. The studies underline that technological developments, in particular the integration of AI, are essential for economic growth and competitiveness. Previous research also highlights that progress in digitalisation and AI developments is essential to stabilising Europe's long-term economic future.

## Industry impact and perspectives of AI

Now that we have analysed the literature on the application of AI in European countries, we will next focus on specific industries and sectors. Below, we look at how AI shapes how different sectors such as transport, healthcare, telecoms, manufacturing and finance operate. We will also look at how AI contributes to increasing efficiency in these industries and to economic and technological progress in general.

In transportation systems, autonomous vehicles and AI-based traffic management systems, as shown in the studies by Abduljabbar et al. (2019) and Haydari–Yilmaz (2022), bring significant efficiency improvements. AI can reduce the cost of traffic congestion by up to $26 billion, while deep reinforcement learning (DRL) algorithms can reduce waiting times by up to 40%. A study by Guo–Wang (2021) also confirms that a combination of model-based predictive control and deep learning can improve traffic management. AI traffic management systems, especially multi-agent systems, can lead to improvements of 20–35%.

In the field of healthcare applications, studies by Agarwal et al. (2024) and Esteva et al. (2019) show that deep learning models such as convolutional neural networks (CNNs) can diagnose skin cancer, diabetic retinopathy and other pathologies with high accuracy. According to Miotto et al. (2017), the processing of unstructured biomedical data can bring significant advances in predictive health systems, and AI systems can improve the accuracy of diagnostic predictions. Tong et al. (2020) also confirm that the application of AI in ophthalmic diagnostics, especially in diabetic retinopathy, is yielding outstanding results.

For the telecom and network industries, studies by Balmer et al. (2020) and Fu et al. (2018) explore the potential of AI applications in traffic management for 5G networks. AI-based traffic management systems can optimise network resources while reducing latency, and data-driven approaches can replace traditional model-based methods.

Morocho-Cayamcela et al. (2019) also emphasise the role of AI and machine learning (ML) technologies in improving spectrum utilization and energy efficiency in 5G/B5G networks. Similarly, studies by Baryannis et al. (2018) and Wang et al. (2020) analyse AI-based risk management in supply chains and 5G networks. Artificial intelligence can be used to provide faster and more adaptive decision making in supply chain risk management, while AI/ML algorithms enable more efficient management of 5G channel measurements.

In the context of manufacturing and financial applications, Wang et al. (2018) and Kullaya Swamy–Sarojamma (2020) show that AI and deep learning technologies can lead to an 82% increase in efficiency in smart manufacturing and improve product quality. Hybridised machine learning algorithms also bring significant accuracy gains in predicting banking transactions.

Taken together, these studies highlight that the application of AI in various industries – be it transport, healthcare, telecommunications, manufacturing or finance – not only leads to efficiency gains, but also brings significant economic benefits, while improving the accuracy of predictive systems and decision-making processes.

## Data collection method and sample characteristics

The data on which our research is based comes from the "ICT usage and e-commerce in enterprises" survey of enterprises in the European Union member states, conducted by national statistical authorities in early 2023 (Eurostat 2023). The survey was designed to provide a comprehensive picture of the use of information and communication technologies (ICT) in enterprises, with a particular focus on the use of AI technologies in enterprises. The methodology and procedures used by the national statistical authorities in the survey ensured that the data were valid and representative of the entire EU enterprise population.

The survey covered the entire population, i.e. enterprises with 10 or more employees in the EU, which included approximately 1.47 million enterprises. To ensure representativeness, 150,400 enterprises were selected for the survey by random sampling. The sampled enterprises were grouped into three main size categories: small enterprises (10–49 employees), medium-sized enterprises (50–249 employees) and large enterprises (250 or more employees). In the sampling process, particular care was taken to ensure that all sizes of enterprises and economic sectors were represented in appropriate proportions so that the results could be widely applicable and comparable.

An important feature of the sampling was the grouping by economic sector, based on the NACE Rev. 2 classification of economic activities. This classification covered a wide range of sectors including manufacturing, information and communication technology, energy, retail trade and professional, scientific and technical services. The survey also provided an accurate picture of the use of ICT and AI technologies in different sectors, which varied considerably by sector and company size.

Data collection was carried out by the national statistical authorities in each member state, which processed the data according to a common methodology. In processing the data, care was taken to ensure that the enterprises in the sample were well represented across the different regions and sectors of the EU, thus ensuring comparability and reliability. Enterprises were analysed according to strict classification systems based on their size and activity, allowing differences between regions to be identified.

The data were analysed using a range of indicators to show how AI has spread across EU businesses. Some charts and tables show percentages, such as the percentage of businesses using AI. Other tables show specific numbers or details on the use of different types of artificial intelligence. The breakdown of the data shows the use of AI by small, medium, and large enterprises, as well as the percentage of each economic sector that uses AI technologies.

The study utilized a range of economic and technological indicators to provide a comprehensive overview of the adoption of artificial intelligence in the European Union. Key indicators included GDP per capita, AI adoption rates, levels of digital skills, and research and development expenditures. These metrics were instrumental in capturing the economic capacity and technological readiness of individual countries, as well as highlighting regional disparities and sectoral differences.

The data was entered into Eurostat's official database after the survey was processed, ensuring EU-wide comparison and access to detailed data for each country. The survey results are widely used for economic analysis, policy making and research.

Table 1 details the percentage of businesses using AI technologies in each country.

Table 1

**Percentage distribution of countries using AI, 2023**

(%)

| Countries | Businesses use at least one of the AI technologies: AL_TTM, AL_TSR, AL_TNLG, AL_TIR, AL_TML, AL_TPA, AL_TAR | Countries | Businesses use at least one of the AI technologies: AL_TTM, AL_TSR, AL_TNLG, AL_TIR, AL_TML, AL_TPA, AL_TAR |
|---|---|---|---|
| European Union | 8.0 | Latvia | 4.5 |
| Austria | 10.8 | Lithuania | 4.9 |
| Belgium | 13.8 | Luxembourg | 14.4 |
| Bosnia and Herzegovina | 5.3 | Malta | 13.2 |
| Bulgaria | 3.6 | Montenegro | 5.6 |
| Croatia | 7.9 | Netherlands | 13.4 |
| Cyprus | 4.7 | Norway | 9.2 |
| Czech Republic | 5.9 | Poland | 3.7 |
| Denmark | 15.2 | Portugal | 7.9 |
| Estonia | 5.2 | Romania | 1.5 |
| Finland | 15.1 | Serbia | 8.0 |
| France | 5.9 | Slovakia | 7.0 |
| Germany | 11.6 | Slovenia | 11.4 |
| Greece | 4.0 | Spain | 9.2 |
| Hungary | 3.7 | Sweden | 10.4 |
| Ireland | 8.0 | Turkey | 5.5 |
| Italy | 5.0 | | |

*Source:* based on Eurostat database own editing.

Table 1 illustrates the extent to which AI technologies are used in each country. The EU average is 8%, but there are significant differences between countries. For example, Denmark (15.2%) and Finland (15.1%) have exceptionally high AI adoption rates, while Romania is at the bottom of the list with only 1.5%. The table also shows that some countries in Central and Eastern Europe, such as Hungary (3.7%) and Poland (3.7%), have lower than average AI adoption rates.

Including non-EU countries such as Turkey, Bosnia and Herzegovina, Montenegro, and Serbia in Table 1 provides a broader perspective on AI adoption trends in the European region. These countries are either official EU candidates or potential candidates, having initiated accession negotiations. Their inclusion reflects their alignment with EU standards and policies, offering valuable insights into how AI technologies are being integrated across the wider European region.

Abbreviations used in Table 1:

- AL_TTM: AI-based text-to-text mining
- AL_TSR: AI-based speech recognition
- AL_TNLG: AI-based natural language generation
- AL_TIR: AI-based image recognition
- AL_TML: AI-based machine learning
- AL_TPA: AI-based process automation
- AL_TAR: AI-based autonomous robotics

In line with the research objectives, this study addresses four key research questions to assess the determinants of AI adoption across EU member states:

**[Q1]:** To what extent does the economic development of a country influence the rate of adoption of AI technologies by companies in the EU member states?

**[Q2]:** To what extent does the level of digitalisation and robotization of a country influence the integration of AI technologies?

**[Q3]:** What factors contribute most to the lower uptake of AI technologies in Central and Eastern European (CEE) countries?

To explore these questions, the study tests the following hypotheses:

**[H1]:** The more developed a country's economy, the higher the share of companies using AI technologies in that country.

**[H2]:** The integration of AI technologies is strongly positively correlated with the level of digitalisation and robotization in a country.

**[H3]:** The lower uptake of AI technologies in CEE countries is mainly due to a weaker technological infrastructure and lower digital skills.

## Statistical analysis for each country

In this chapter, we look at the uptake of AI in the European Union countries in 2023. Statistical and cluster analysis methods are used. The aim is to explore differences and similarities in the use of artificial intelligence across EU member states. We also examine the economic and technological factors influencing the adoption of AI. The analyses will help to better understand the differences between countries. The research will be useful in identifying regional challenges that may hinder the uptake of AI.

### Correlation analysis

A more detailed analysis of the correlation matrix (Table 2) provides an opportunity to understand the relationship between different AI technologies. In the following, we discuss in more detail the strong, medium and weak correlations, their possible causes and general conclusions.

Table 2

## Correlation matrix

| | | Speech recognition | Natural language generation | Image recognition | Machine learning | Robotic process automation | Autonomous drones | Marketing | Production | Logistics | ICT security |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Text mining | Pearson correlation | 0.801** | 0.325 | 0.402* | 0.750** | 0.779** | 0.469* | 0.583** | 0.613** | 0.624** | 0.346 |
| | Sig. (2-tailed) | 0.000 | 0.098 | 0.038 | 0.000 | 0.000 | 0.014 | 0.001 | 0.001 | 0.001 | 0.077 |
| | N | 27 | 27 | 27 | 27 | 27 | 27 | 27 | 27 | 27 | 27 |
| Speech recognition | Pearson correlation | | 0.524** | 0.562** | 0.610** | 0.633** | 0.494** | 0.460* | 0.594** | 0.591** | 0.470* |
| | Sig. (2-tailed) | | 0.005 | 0.002 | 0.001 | 0.000 | 0.009 | 0.016 | 0.001 | 0.001 | 0.013 |
| | N | | 27 | 27 | 27 | 27 | 27 | 27 | 27 | 27 | 27 |
| Natural language generation | Pearson correlation | | | 0.667** | 0.572** | 0.461* | 0.463* | 0.630** | 0.653** | 0.537** | 0.900** |
| | Sig. (2-tailed) | | | 0.000 | 0.002 | 0.015 | 0.015 | 0.000 | 0.000 | 0.004 | 0.000 |
| | N | | | 27 | 27 | 27 | 27 | 27 | 27 | 27 | 27 |
| Image recognition | Pearson correlation | | | | 0.418* | 0.522** | 0.514** | 0.421* | 0.807** | 0.661** | 0.724** |
| | Sig. (2-tailed) | | | | 0.030 | 0.005 | 0.006 | 0.029 | 0.000 | 0.000 | 0.000 |
| | N | | | | 27 | 27 | 27 | 27 | 27 | 27 | 27 |
| Machine learning | Pearson correlation | | | | | 0.878** | 0.696** | 0.763** | 0.773** | 0.817** | 0.655** |
| | Sig. (2-tailed) | | | | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | N | | | | | 27 | 27 | 27 | 27 | 27 | 27 |
| Robotic process automation | Pearson correlation | | | | | | 0.749** | 0.726** | 0.771** | 0.818** | 0.550** |
| | Sig. (2-tailed) | | | | | | 0.000 | 0.000 | 0.000 | 0.000 | 0.003 |
| | N | | | | | | 27 | 27 | 27 | 27 | 27 |
| Autonomous drones | Pearson correlation | | | | | | | 0.536** | 0.662** | 0.828** | 0.504** |
| | Sig. (2-tailed) | | | | | | | 0.004 | 0.000 | 0.000 | 0.007 |
| | N | | | | | | | 27 | 27 | 27 | 27 |
| Marketing | Pearson correlation | | | | | | | | 0.670** | 0.673** | 0.556** |
| | Sig. (2-tailed) | | | | | | | | 0.000 | 0.000 | 0.003 |
| | N | | | | | | | | 27 | 27 | 27 |
| Production | Pearson correlation | | | | | | | | | 0.865** | 0.763** |
| | Sig. (2-tailed) | | | | | | | | | 0.000 | 0.000 |
| | N | | | | | | | | | 27 | 27 |
| Logistics | Pearson correlation | | | | | | | | | 1 | 0.637** |
| | Sig. (2-tailed) | | | | | | | | | | 0.000 |
| | N | | | | | | | | | | 27 |

*Note:* *correlation is significant at the 0.05 level (2-tailed), ** correlation is significant at the 0.01 level (2-tailed).
*Source:* based on Eurostat database own editing.

All correlations are significant at the 5% level ($p < 0.05$), except for the correlations between ***text mining*** and ***ICT security*** ($r = 0.346$), and text mining and natural language generation ($r = 0.325$), which are not statistically significant. These findings highlight the lack of a robust relationship between these pairs of variables, suggesting that these technologies operate in distinct domains with minimal interaction. This is particularly relevant for understanding where synergies might not exist, helping to focus future research efforts on areas with stronger interconnections. The non-significant correlations have been explicitly marked to provide clarity and aid in interpreting the analysis results.

Let's first analyse the relationships between the three technologies with the strongest correlation. ***Machine learning (ML)*** is one of the core technologies used in ***robotic process automation (RPA)***. Not surprisingly, the strongest correlation ($r = 0.878$) was identified between them. RPA offers the potential to automate repetitive, structured tasks using patterns and algorithms learned through machine learning. RPA systems are often based on ML models that can continuously learn and optimise processes. The strong correlation shows that these technologies are closely linked and, working together, can achieve significant efficiency gains in industrial and business processes.

***Text mining*** and ***speech recognition*** are closely related, as they both focus on the processing of linguistic data. The correlation between them is ***r = 0.801***. In speech recognition, spoken language is converted into textual form, which can be further analysed in text mining. These two technologies are often used in pairs, for example, in voice command systems, where further text data is mined from the analysed speech. This strong correlation suggests that where speech recognition is used at a high level, text mining is likely to play a significant role, as the output of one technology can serve as input to the other.

The link between ***marketing*** and ***production*** is primarily rooted in the fact that both are closely linked to the market penetration of products. With ***r = 0.763***, the correlation between them is the third highest. AI techniques in marketing, such as targeted advertising, forecasting, and analysis of consumer behaviour, are often based on manufacturing data. Analysis of manufacturing data helps to develop and refine marketing strategies. This strong correlation suggests that marketing decisions are often based on data from manufacturing processes, so where advanced manufacturing AI technologies are used, marketing can also rely heavily on AI.

Let's now look at technologies with moderately strong correlations. Here again, we highlight the three with the highest values. ***Machine learning*** is a fundamental method of ***text mining***. The correlation between them is ***r = 0.750***. In text mining, text data is analysed using machine learning algorithms to extract valuable information. For example, text categorisation, sentiment analysis, and keyword identification rely on ML. The moderate strength of correlation suggests that although text mining and machine learning are related, there may be other factors that influence the effectiveness of text mining, such as the quality of the language model or the amount of data used.

The correlation between ***image recognition*** and ***logistic*** is also moderately strong ***(r = 0.724)***. Imaging techniques, in particular image recognition, play a key role in logistics, for example in package identification, inventory management and quality control. Image recognition can automate a large part of logistics processes, increasing efficiency and reducing human error. The medium correlation suggests that image recognition plays a significant, but not exclusive, role in logistics. Its effectiveness depends on the scope of the technology and the quality of integration.

Finally, the relationship between the technologies with the lowest correlation is analysed. The weak correlation between ***text mining*** and ***ICT security (r = 0.346)*** suggests that these technologies are less directly related. ICT security is mainly focused on protecting networks, systems and data, while text mining is more concerned with data interpretation and analysis. The lack of correlation also shows that these technologies are used in different application areas. This weak correlation indicates that text mining does not necessarily have a direct impact on ICT security and vice versa.

It is important to note that correlation does not necessarily mean causation. The existence of a strong correlation between two variables does not automatically mean that a change in one variable directly causes a change in the other variable. It is also possible that a third variable (e.g. technological developments, industry trends) is involved in the observed relationship. The p-values indicate how statistically reliable the correlation is. If the p-value is less than 0.05, the correlation is considered significant, meaning that it is unlikely to be due to chance. A p-value of less than 0.01 means even more stringent significance. Significant correlations suggest that the observed relationship is likely to be real and it is worth further investigation to find out the exact reasons.

Correlations between different AI technologies can help us understand which technologies work well together and how they support each other in industrial applications. For example, the strong correlation between machine learning and robotic process automation suggests that these technologies together can make processes more efficient.

After examining the correlation matrix, it is worth looking in detail at the value of the **determinant** of the matrix, which plays a fundamental role in understanding the properties and behaviour of the matrix. This value is of particular importance in the preparation of factor analysis, as it indicates the degree of invertibility of the matrix. The correlation matrix itself shows the relationships between the variables and the determinant value is a quantified indicator that helps to understand how stable the matrix is and how it can be used for further analysis.

The value of the determinant of the correlation matrix under study is extremely low, specifically $4.83 \times 10^{-7}$, which suggests that the matrix is nearly singular. This near-singularity indicates that there is a strong multicollinearity between the variables, i.e. the variables are significantly correlated. Such strong correlations can cause problems in factor analysis, as it can make it difficult to clearly separate factors and to ensure the stability of results. A low determinant value is a warning sign that challenges may arise in factor analysis, especially if the information content of the matrix is redundant and the correlations between variables are too similar. In such cases, analysts may wish to consider reducing the number of variables or using alternative statistical methods such as principal component analysis (PCA), which can more effectively deal with multicollinearity and improve the reliability of results.This detailed study will help to prepare for further analyses to assess the strength and reliability of correlations, as well as to gain a deeper understanding of the relationships between different AI technologies. For example, strong correlations may suggest that certain technologies work in close cooperation and may therefore be particularly effective in industrial applications.

Now let's examine the effect of different variables on a dependent variable using **linear regression**. The results show that the strength and significance of the effect of each independent variable varies. The constant plays a significant role in the model. If all the independent variables are zero, the expected value of the dependent variable will be 28.106. This value is highly significant, which means that this part of the model provides a reliable basis for interpreting the results. The results suggest a negative effect for the speech recognition variable. If the value of speech recognition increases by one unit, the value of the dependent variable decreases by approximately 1.789 units. This result is statistically significant, so the speech recognition variable reliably explains the dependent variable. The natural language generation variable also has a slight negative effect, but this is not significant. This means that the natural language generation variable does not have a statistically significant effect on the dependent variable, so no firm conclusion can be drawn from this result. The machine learning variable also has a negative effect, but this result is also not significant. In addition, the multicollinearity test suggests that machine learning is strongly correlated with other independent variables, which may bias the results. This high correlation may suggest that there is an overlap between variables, which reduces the reliability of the model. The autonomous drones variable shows a significant negative effect. This means that when the value of the autonomous drones variable increases, the value of the dependent variable decreases. This result is statistically reliable, so the inclusion of this variable in the model is important. The effect of the marketing variable is not significant, which means that marketing does not have a significant effect on the dependent variable. As a consequence, marketing can be ignored when further refining the model. The production variable has a strong negative effect on the dependent variable and this result is significant. This indicates that as production increases, the value of the dependent variable decreases significantly, so the role of this variable is important in the model. The multicollinearity test shows that the variables machine learning and manufacturing are highly correlated with other independent variables. This means that these variables contain similar information, which may bias the model results. The high correlation may warn that certain variables may need to be dropped from the model to improve the reliability of the results.

The analysis has revealed that speech recognition, autonomous drones and manufacturing variables significantly affect the dependent variable. In contrast, natural language generation, machine learning and marketing show no significant effect. The presence of multicollinearity indicates a strong relationship between certain variables, which may bias the results. It may therefore be worthwhile to treat these variables separately when refining the model.

It is also important to examine **multicollinearity**. In the analysis, the diagnostic results of multicollinearity showed that different dimensions affect the variance of the independent variables differently. In the case of the ***first dimension***, where the eigenvalue is prominently high, the variance ratios for all variables show values around zero, indicating that this dimension does not contribute to explaining the variance of the independent variables. The conditionality index of the ***second dimension*** shows some relationship, especially for the variables "natural language generation" and "machine learning", although the degree of these relationships is still low. This suggests that in this dimension these variables have a minimal impact on the variance of the model. In the ***third dimension***, "natural language generation" shows a higher variance, suggesting that this variable is more closely related to the dimension, while the other variables are only moderately related. This relationship may be important for further analysis of the model. For the ***fourth dimension***, the variance ratio for "speech recognition" is high, suggesting that this variable is strongly correlated in this dimension. This is a clear indication that the role of the speech recognition variable is significant in this context. In the ***fifth dimension***, the variables "machine learning" and "autonomous drones" are related to this dimension in similar proportions, indicating multicollinearity between these variables. The strong correlations of these variables indicate that they may bias the results if they are not treated appropriately. In the ***sixth dimension***, the strongest correlations are mainly observed for the variables "manufacturing" and "marketing". The variable "production" shows a particularly high variance, indicating a strong correlation with other variables in this dimension, which further strengthens the possibility of multicollinearity. Finally, in the ***seventh dimension***, the variables "machine learning" and "manufacturing" show high variance ratios, indicating a strong relationship between these variables. This suggests that these variables are highly correlated with each other, which may also cause a multicollinearity problem in the model.

Overall, the analysis clearly shows that certain variables, such as "machine learning" and "manufacturing", show a strong relationship with certain dimensions, suggesting multicollinearity. These variables may bias the results of the model and it would be worthwhile to refine the model to reduce the effect of multicollinearity.

## Principal component analysis

Principal component analysis (PCA) is a statistical method that reduces the variance in a data set to a few principal components while preserving the most important information in the data. This method is particularly useful when working with a large number of variables and the aim is to reduce dimensions and reveal underlying structures. In PCA, relationships between the original variables are organised into new, independent components that explain as much variance in the data as possible.

The results show that the eigenvalue of the first component in the principal component analysis is 7.317, which means that this component explains 66.5% of the total variance. This suggests that the first component is the most important dimension in explaining the data. The second component has an eigenvalue of 1.261, which accounts for 11.5% of the variance. Together, the first two components explain 78% of the total variance, indicating that these components dominate the explanation of the data structure. Based on the rotated sum of squares, the first component explains 44.768% and the second component explains 33.215%. Thus, in the rotated solution, the first two components together account for 77.983% of the explanatory power, which covers a significant proportion of the total data structure. The rotated solution helps to better separate the explanatory power between the components, thus improving the interpretability of each component in the analysis.

Based on the PCA results, we identified six variables that most significantly contributed to the explanation of the variance across countries. These variables – covering both visual and linguistic AI technologies – showed high loadings on the two principal components and represented the most relevant aspects of AI integration. As a result, these six variables were selected for the subsequent stages of the analysis, including hierarchical clustering and multidimensional scaling. This selection ensures methodological consistency and allows for a coherent comparison of countries throughout the entire study.

Table 3

**Rotated component matrix**

| | Component | |
|---|---|---|
| | 1 | 2 |
| **Natural language generation** | **0.903** | 0.158 |
| **Image recognition/image processing** | **0.810** | 0.244 |
| **Marketing** | **0.611** | 0.483 |
| **Autonomous drones** | **0.596** | 0.445 |
| Text mining | 0.174 | **0.956** |
| Speech recognition | 0.372 | **0.825** |

*Source:* based on Eurostat database own editing.

Statistical analysis of the rotated component matrix (Table 3) identified two principal components that discriminate well between variables based on explained variance.

Component 1 is dominated by the variable "natural language generation", which has the highest loading on this component (0.903). This indicates that natural language generation is strongly related to component 1 and represents a significant part of the data structure. Likewise, the variable "image recognition and processing" has a high loading on component 1 (0.810), indicating that this technology is also strongly linked to the first dimension. The variables "marketing" (0.611) and "autonomous drones" (0.596) are also related to component 1, although with a weaker loading, suggesting that these technologies are also related to this dimension, but less dominant.

Component 2 is most strongly explained by the variables "text mining" (0.956) and "speech recognition" (0.825). Both variables have a significant loading on this component, indicating that these technologies are closely related to the second component and are more likely to be interpreted through it.

The statistical analysis suggests that rotation helped to separate the variables between the two components better. The first component focuses mainly on visual technologies (image recognition) and marketing-related variables, while the second component focuses more on text analysis technologies (text mining and speech recognition). This type of separation contributes to improving the interpretability of the variables by organising them into a clearer structure.

The distribution of the variables across the components shows that the technology categories are well differentiated: visual and language technologies are associated with separate components, which allows statistically valid conclusions to be drawn.

## Cluster analysis

In this study, hierarchical clustering was employed to analyse the relationships between European countries based on AI adoption levels. The dendrogram method was specifically chosen because it provides a clear visualization of how countries split into clusters at different thresholds. The 0.25 similarity level was selected as the cut-off point, as it effectively differentiates the clusters based on regional and technological similarities. This allows the analysis to focus on meaningful groupings that reflect shared characteristics in AI adoption.

Hierarchical clustering was utilized instead of other methods, such as *k*-means clustering because the dendrogram enables detailed exploration of relationships across various levels of similarity. This visualization makes it easier to observe at which similarity levels the clusters form and separate, providing a comprehensive understanding of how countries align or diverge in terms of AI technology integration.

The choice of hierarchical clustering also aids in identifying levels of separation that are most relevant for interpreting the data, such as at the 0.25 threshold, where distinct regional patterns become evident. This method is particularly suitable for studying regional trends and understanding the broader dynamics of AI adoption in the European region.

To further investigate the interrelationships between the six selected variables identified through PCA, an inverse correlation matrix was constructed (Table 4). The variables were rescaled to the 0–1 interval to ensure comparability and reduce scale-related distortions. This standardisation allows for a more meaningful interpretation of the relationships among variables and supports the robustness of subsequent clustering procedures.

Table 4

**Inverse correlation matrix**

| | Text mining | Speech recognition | Natural language generation | Image recognition/ image processing | Autonomous drones | Marketing |
|---|---|---|---|---|---|---|
| Text mining | **4.475** | –3.475 | 1.772 | –0.153 | –0.026 | –2.047 |
| Speech recognition | –3.475 | **4.386** | –1.617 | –0.403 | –0.312 | 1.362 |
| Natural language generation | 1.772 | –1.617 | **3.198** | –1.213 | 0.101 | –1.847 |
| Image recognition/ image processing | –0.153 | –0.403 | –1.213 | **2.194** | –0.502 | 0.384 |
| Autonomous drones | –0.026 | –0.312 | 0.101 | –0.502 | **1.702** | –0.606 |
| Marketing | –2.047 | 1.362 | –1.847 | 0.384 | –0.606 | **2.893** |

*Source:* based on Eurostat database own editing.

In the matrix, inverse correlation values indicate how the relationship between variables changes when controlling for other variables. The diagonal elements show the "self-correlation" of the variables, i.e. how independent the variables are from other variables. Diagonal values are all greater than 1, indicating that each variable has significant information relative to the others.

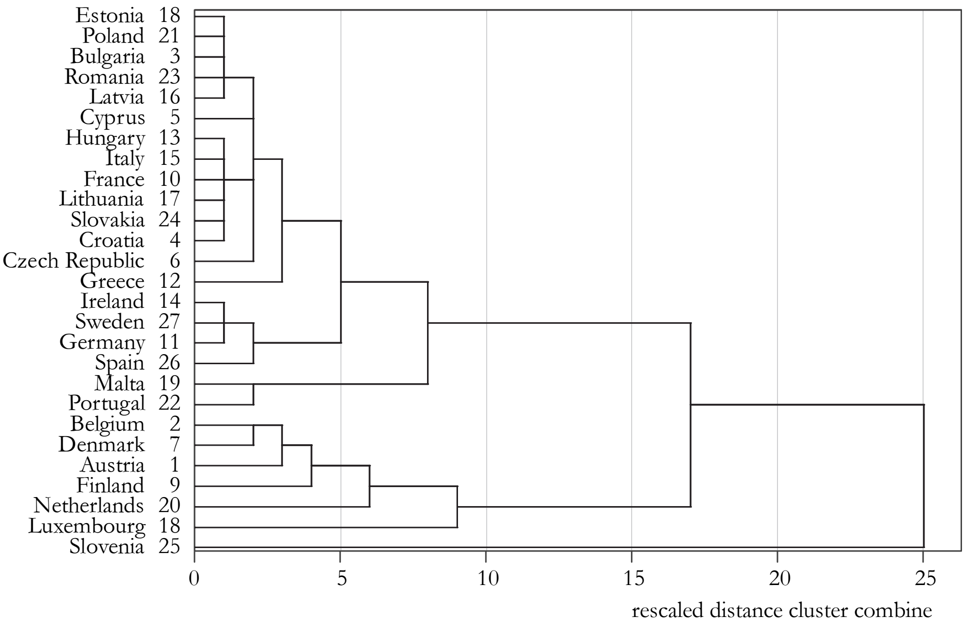
1. **Text mining**: Its own correlation value is 4.475, showing a strong relationship, while it is negatively related to "speech recognition" (–3.475) and "marketing" (–2.047). This means that when controlling for *word mining*, these variables behave in opposite directions to each other.
2. **Speech recognition**: Its own correlation value is 4.386, which also indicates strong information content. It is strongly but negatively correlated with "text mining" (–3.475) and "natural language generation" (–1.617), i.e. when one is controlled, the other is less explainable.
3. **Natural language generation**: This variable has an eigenvalue of 3.198, indicating a moderately strong independence. It shows a strong but negative relationship with "image recognition" (–1.213) and "marketing" (–1.847).

4. **Image recognition/image processing**: Its own value is 2.194, relatively lower than the other variables but still significant. This variable is less correlated with the other variables, but shows a negative correlation with "speech recognition" (–0.403) and "text mining" (–0.153).
5. **Autonomous drones**: This variable has an eigenvalue of 1.702, which is the lowest correlation with the other variables, suggesting that this variable is less correlated with the other variables. It has a slight negative correlation with "speech recognition" (–0.312) and "image recognition" (–0.502).
6. **Marketing**: This variable is moderately strongly correlated with its own correlation value (2.893) and is closely related to "text mining" (–2.047) and "natural language generation" (–1.847), with which it has a significant but negative relationship.

European countries can also be assessed on the basis of their level of use of AI technologies. The dendrogram in Figure 1 shows the result of a hierarchical clustering procedure using the average connectivity between groups method. The figure illustrates the analysis of similarities and differences between different countries, where distances between countries were rescaled to combine clusters. The purpose of the dendrogram is to provide a visual representation of how countries can be grouped according to their common characteristics and the extent to which they differ from each other. The relationships between each cluster and the process of clustering are reflected in the distance values displayed on the vertical axis.

Figure 1

**Dendogram**




*Source:* based on Eurostat database own editing.

The **dendrogram**, which shows the results of a cluster analysis of European countries based on their use of AI technologies, identifies three main clusters. These clusters reflect the different levels at which each country is applying and integrating AI technologies into their economies and businesses.

The countries in the ***first cluster***, including Austria, Belgium, Denmark, Finland, Luxembourg, the Netherlands, Sweden and Denmark, are all advanced economies with outstanding technological infrastructures and significant innovation capacity. These countries are leaders in the adoption and use of AI technologies, which gives them an advantage in remaining competitive in global markets. The integration of AI technologies in these countries is already pervasive across a wide range of industries and services and plays a key role in automation, predictive analytics and the provision of personalised services.

The countries in the ***second cluster***, such as Hungary, Italy, France, Poland and others, have typically integrated AI technologies to a more moderate extent. Economically, these countries are diverse but face different barriers to widespread adoption of AI. These barriers may include less developed technological infrastructure, lower levels of digital skills in the labour market, or inflexible regulatory environments. The application of AI technologies in these countries is often more limited than in the first cluster countries, and developments are mainly concentrated in a few key sectors such as finance or automotive.

The ***third cluster*** includes only Slovenia, suggesting that this country is significantly different from the other countries surveyed in some respects. Slovenia's emergence as a distinct cluster may indicate that it faces unique challenges or even opportunities in the application of AI technologies. Although it has a certain level of technological infrastructure and digital skills, the integration and exploitation of these do not present a consistent picture as in other countries, which creates a unique situation in the uptake and use of AI technologies.

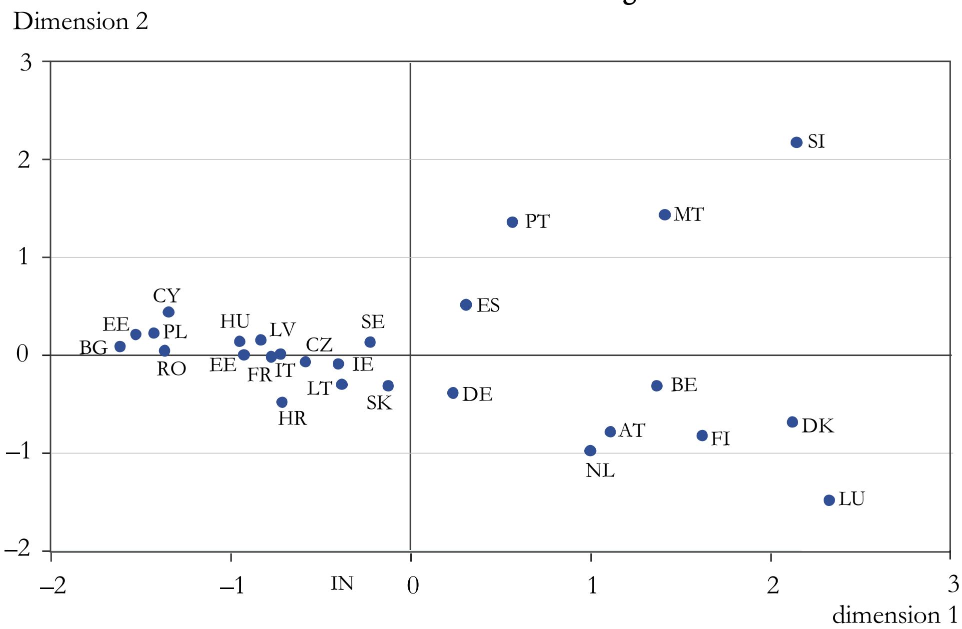
A number of factors may underlie the emergence of clusters, including economic development, the quality of education systems, support for government policies, and the openness and innovation capabilities of the corporate sector to AI. The countries in the first cluster are likely to play a leading role in the global market for AI-based innovations and can further strengthen their positions by continuously improving their technological capabilities. For the countries in the second cluster, developing infrastructure and digital skills, as well as broadening the application of AI technologies in different economic sectors, could be key. Slovenia's unique situation may justify further research to better understand the local challenges and opportunities for the adoption of AI technologies. Overall, the results of the cluster analysis can help to develop more targeted strategies to enhance AI integration in each country, taking into account their specific situation and potential. The clusters thus reflect differences in the uptake of AI technologies across European countries, which vary according to economic development, industrial structure and the maturity of the innovation ecosystem. We recommend that future research should investigate the specific factors that influence the AI technology readiness of the countries in each cluster and how to promote innovation in less developed regions.

## Multidimensional scaling (MDS)

The multidimensional scaling (see Figure 2) displays countries in a two-dimensional space, which helps to visualize and interpret differences in economic and technological indicators based on the level of AI integration.

Figure 2

**Multidimensional scaling**




*Source:* based on Eurostat database own editing.

The data for our analysis were sourced from the 2023 Eurostat database, specifically the ICT usage and e-commerce in enterprises survey. We included indicators such as GDP per capita, AI adoption rates, digital skill levels, and R&D expenditure to capture economic capacity and technological potential. GDP per capita was used as the primary economic indicator, offering a more nuanced perspective on individual economic performance and better reflecting disparities across regions.

The x-axis represents the technological advancement and the extent of AI integration in each country. This dimension incorporates variables such as the percentage of enterprises using AI technologies (e.g., machine learning, text mining, speech recognition), and the level of digital skills among the workforce. These indicators reflect how deeply embedded AI is in operational processes and how advanced the technological environment is in a given country.

The y-axis reflects the broader economic and innovation environment in which AI technologies are applied. This includes GDP per capita as a proxy for economic development, R&D expenditure as a measure of innovation capacity, and digital skill levels as an indicator of technological readiness. While individual values of these variables are not presented in separate tables, they were included as aggregated indicators in the multidimensional scaling model to represent countries' economic and technological environment.

The figure shows the result of an MDS that places European countries along two dimensions based on the Euclidean distance model. The variables included in the model were selected based on the results of the PCA, which identified the most informative indicators of AI integration across countries. This ensured methodological consistency across the analytical steps and allowed for a coherent interpretation of both clustering and scaling results. The $R^2$ value of the MDS model is also an important factor in this analysis, as it indicates the extent to which the model can explain the variance between the data. The closer $R^2$ is to 1, the better the model explains the variance. In this case, the MDS model has a relatively high $R^2$ value, indicating that the distances between countries in the two-dimensional space reliably reflect the differences in the original dataset. The aim was to visualize these differences using a simplified but statistically validated model.

Based on the distribution of countries, four distinct quadrants can be identified in the two-dimensional space. These quadrants reflect both the level of technological development (x-axis) and the economic and innovation potential (y-axis), and help to better interpret regional differences in AI integration across Europe.

**Quadrant I (positive x and positive y values)**: This group includes countries such as Slovenia, Malta, and Portugal, which exhibit both high levels of technological advancement and strong economic and innovation capacity. These countries serve as examples of balanced progress, where favourable economic conditions are accompanied by ambitious and effective AI integration strategies. Their position in the top-right quadrant reflects robust digital infrastructure, widespread adoption of AI tools, and consistent investment in research and innovation.

**Quadrant II (negative x and positive y values)**: Countries such as Estonia, Cyprus, Poland, Hungary, and Latvia are located in this quadrant. Despite their relatively limited technological integration in terms of AI deployment, these countries demonstrate solid economic performance and innovation potential. This positioning suggests that while structural capacity for technological advancement exists, the actual implementation and integration of AI may still be in development. These nations could benefit from targeted digitalisation policies and institutional support to unlock their latent AI potential.

**Quadrant III (negative x and negative y values)**: This quadrant includes countries such as Romania, Bulgaria, Croatia, Lithuania, and Slovakia, which face challenges in both technological and economic dimensions. They typically lag behind the EU average in terms of AI adoption, digital skill levels, and R&D investment. Their position reflects structural constraints and highlights the persistence of regional disparities in digital readiness and innovation within the European Union. These countries require comprehensive policy interventions to foster both economic growth and digital transformation.

**Quadrant IV (positive x and negative y values)**: This area is characterised by countries such as Luxembourg, Denmark, Finland, the Netherlands, and Austria, which demonstrate advanced technological capabilities and high AI integration, despite weaker scores in the economic and innovation dimension of the model. This may be the result of sectoral imbalances, specific data-driven anomalies, or the decoupling of digital ambition from broader economic indicators. These cases illustrate that technological excellence can sometimes be achieved even in contexts where overall economic performance appears relatively moderate.

In summary, the quadrant-based interpretation provides a more nuanced understanding of regional AI adoption in the EU. It highlights the complexity of AI integration, which depends not only on economic strength but also on digital maturity, institutional support, and public acceptance. These insights can help shape targeted policy interventions across different country groups.

## Discussion

We compare our findings with relevant prior research on the application of artificial intelligence and digital technologies. Particular focus is given to topics such as digital transformation, the development of e-commerce, and the spatial distribution of educational potential. The analyses highlight disparities in digital maturity, e-commerce advancement, and innovation investments across European countries. Simultaneously, we demonstrate how AI can contribute to optimising these processes and addressing existing challenges, offering a new perspective on enhancing competitiveness and reducing regional inequalities.

### Comparison with relevant research

We review prior studies closely related to our research, focusing on digital transformation, e-commerce development, and the spatial distribution of educational potential. These analyses provide a framework to compare our findings and position them within the broader academic context. The reviewed studies offer valuable insights into the disparities in digital maturity across European countries, the digital divide in e-commerce, and the regional distribution of education and innovation investments. Building on these foundational works, our research introduces a novel perspective by emphasising the role of artificial intelligence in optimising these processes. We explore how AI can contribute to reducing regional inequalities and enhancing competitiveness by addressing key challenges in education, innovation, and digital transformation.

The study by Huňady et al. (2024) explores the digital transformation of businesses in European Union countries before and during the Covid-19 pandemic, focusing on changes in digital readiness. The authors employ factor analysis and hierarchical cluster analysis using Eurostat data to classify EU countries into clusters based on their digital maturity. The results reveal that while the most digitally advanced countries, such as Belgium, Denmark, Finland, and the Netherlands, retained their leadership positions, others, like Estonia, Latvia, and Slovenia, made notable progress during the pandemic. Conversely, countries with traditionally low digital readiness, such as Bulgaria, Romania, and Hungary, remained in the lowest-performing clusters. The study highlights the role of the pandemic as a disruptive force that accelerated digital adoption, particularly in cloud computing, remote work solutions, and e-business tools. However, stagnation or slight decline was observed in the use of advanced technologies, such as big data analytics and service robots.

The study's findings align closely with our research, which examines not only digital transformation but also the role of AI in advancing businesses' digital maturity. While the analysed work highlights the adoption of fundamental digital tools – such as cloud computing and e-commerce platforms – our research explores the deeper integration of AI-driven technologies, including advanced data analytics, predictive systems, and process automation, as key enablers of digital readiness. The observed regional disparities in digital transformation, particularly in lagging countries like Hungary and Bulgaria, reinforce our conclusion that strategic deployment of AI can bridge these divides. For instance, AI applications in big data analytics can empower businesses to generate actionable insights even in regions with limited digital infrastructure. Moreover, while the study provides a macro-level classification of countries, our research takes an industry-specific perspective, offering a detailed analysis of how AI adoption can enhance competitiveness and resilience across various sectors. By building on this foundational analysis of digital transformation, our study demonstrates the transformative potential of AI technologies in achieving sustainable digital and operational advancement.

The study by Jaković et al. (2021) investigates disparities in e-commerce functionalities among enterprises in European Union countries, focusing on the concept of the digital divide. Using 2019 Eurostat data and *k*-means clustering analysis, the authors identify three homogeneous groups: highly developed, developed, and developing countries. The results indicate that highly developed nations, such as Scandinavian and Benelux countries, excel in e-commerce functionalities, while developing countries, predominantly in Eastern Europe, lag behind. The study highlights that the relationship between economic development and e-commerce progress is non-linear, suggesting that policy decisions significantly influence e-commerce adoption. The research assesses website functionalities (e.g., chatbots, pricing information) and the use of customer relationship management (CRM) systems, emphasising their importance in the digital economy.

The study's findings on the relationship between e-commerce functionalities and the digital divide provide a strong basis for our research. While the analysis focuses on varying levels of digital technology adoption across Europe, our work advances this perspective by emphasising the integration of AI technologies. Solutions such as advanced CRM analytics, recommendation systems, and automated chatbots not only enhance enterprise functionalities but also play a crucial role in reducing the digital divide. For developing countries, AI-powered digital tools can serve as catalysts for growth, helping businesses bridge technological gaps. In alignment with this, our research explores how artificial intelligence can drive corporate competitiveness within e-commerce and the broader digital economy.

Dubrovina et al. (2023) examine the spatial characteristics of educational potential and innovation investments in Central and Eastern European regions. Using Eurostat data, spatial econometric models, statistical analyses, and cluster methodologies, the study explores the relationship between education levels and innovation investments in the Nomenclature of Territorial Units for Statistics level 2 (NUTS 2) regions. The findings highlight the significant impact of educational potential and innovation on the flexibility of regional labour markets while identifying barriers such as regional income inequalities and weak institutional support for public education, which hinder competitiveness. The study concludes that the spatial distribution of education and innovation is non-linear and significantly influenced by economic and socio-political factors. This research emphasises the critical link between education, innovation, and economic development for the long-term sustainability of regions.

This study intersects with our research focus on the interrelation between education, innovation, and economic development, particularly in addressing regional disparities. While Dubrovina et al. (2023) analyse the spatial inequalities and the impact of educational potential and innovation investments, our work investigates the role of artificial intelligence in enhancing education and innovation systems. AI provides opportunities to personalise educational programmes, automate and optimise innovation processes, and improve efficiency, particularly in regions affected by income disparities. Furthermore, AI-driven predictive models and data science tools can be employed to identify labour market challenges and allocate resources more effectively, thereby contributing to reducing regional inequalities and fostering competitiveness.

The reviewed studies are closely aligned with the focus of our research, which examines the role of AI in driving digital transformation, enhancing e-commerce, and advancing educational and innovation systems. The findings from these earlier studies confirm that disparities in digital maturity, e-commerce development, and regional educational potential significantly influence competitiveness and sustainable development across Europe. Building on these insights, our research explores how AI can bridge technological gaps, automate innovation processes, and enhance digital maturity across regions and industries. By addressing existing challenges, our work not only contributes to the theoretical understanding of these issues but also proposes practical applications to strengthen the digital economy and foster long-term growth.

## Contributions to theory and literature

This study advances the understanding of artificial intelligence adoption across the European Union, particularly in relation to economic development and digital infrastructure. While previous research has focused on isolated aspects of AI integration – such as its economic impacts or digital maturity – this study provides a comprehensive framework linking these dimensions. By employing advanced statistical methods, including correlation analysis, principal component analysis, and hierarchical clustering, the research uncovers key patterns in the adoption of AI technologies such as machine learning, robotic process automation, and text mining. These findings enrich the existing literature by highlighting the synergies and dependencies between different AI technologies and their economic applications. Furthermore, the study emphasises the critical role of technological readiness and regional disparities, contributing to broader theoretical discussions on digital transformation and innovation.

## Implications for practice

The findings of this research have significant practical implications for policymakers, business leaders, and stakeholders in the digital economy. A key insight is that AI technologies – particularly machine learning and robotic process automation – are fundamental to enhancing operational efficiency and driving innovation. For policymakers, the results underscore the importance of investing in digital skills development and technological infrastructure, especially in less developed regions such as Central and Eastern Europe. Initiatives aimed at bridging the digital divide – such as targeted educational programmes, financial incentives for AI adoption, and strategic regulatory reforms – can accelerate AI integration and reduce regional disparities.

For businesses, the analysis highlights the transformative potential of AI in optimising processes across various industries, from manufacturing to e-commerce and healthcare. Companies operating in countries with lower or moderate AI adoption rates can use these findings to identify AI solutions best suited to their specific needs. Tools such as predictive analytics and automated systems offer scalable opportunities to improve productivity and competitiveness, even in resource-constrained environments.

The study also suggests strategies for strengthening cross-border collaboration within the EU. By aligning the technological strengths of advanced economies, such as those in Scandinavia, with the untapped potential of less developed regions, stakeholders can foster a more unified and inclusive digital ecosystem. Additionally, the strong technological correlations identified in the analysis provide practical guidance for businesses on which AI technologies to prioritise during integration efforts. This can be supported through existing EU-level programmes – such as Horizon Europe, the Digital Europe Programme, the European Innovation Council (EIC), and the Connecting Europe Facility (CEF). These initiatives provide funding for joint research projects, innovation partnerships, and the development of AI-related infrastructure across borders. In addition to direct financial support, they offer frameworks for transnational collaboration, foster the establishment of European Digital Innovation Hubs (EDIHs), and encourage public-private partnerships. Moreover, initiatives like the European AI Alliance and the AI-on-Demand Platform facilitate knowledge sharing, the dissemination of best practices, and cross-border policy harmonisation. Coordinated AI deployment, particularly in areas such as public services, healthcare, and smart industry, can be enhanced through targeted pilot projects, regional twinning schemes, and capacity-building programmes. These instruments play a crucial role in bridging the east–west innovation gap and in ensuring that digital transformation efforts reach all regions of the EU in a balanced and inclusive manner. By addressing regional and industry-specific challenges, this research equips decision-makers with targeted strategies to promote AI adoption, thereby contributing to the EU's long-term economic growth and technological innovation.

## Conclusion

The study was guided by three research questions:

- **RQ1:** Are there significant differences in AI adoption across EU member states based on their economic development and digital capabilities?
- **RQ2:** How are digitalisation and robotization levels related to the integration of AI technologies across different countries?
- **RQ3:** What are the main technological or structural barriers in Central and Eastern European countries that hinder the adoption of AI technologies?

The following hypotheses were formulated to address these questions and tested through empirical analyses:

**H1:** The analysis confirms that economically developed countries, such as Denmark (15.2%), Finland (15.1%), and Luxembourg (14.4%), exhibit significantly higher AI adoption rates compared to less developed regions like Romania (1.5%)

and Bulgaria (3.6%). Cluster analysis placed the more developed countries into a separate high-performing group, highlighting their advanced technological infrastructure and innovation capacity. Conversely, less developed countries show significantly lower AI adoption rates, reflecting considerable technological and economic lag. These results strongly correlate with GDP levels and digital competencies, supporting the validity of this hypothesis.

**H2:** Correlation analysis demonstrates a strong positive relationship between digitalisation and AI integration. For example, Denmark, where digital skill levels are exceptionally high (97%), also has an AI adoption rate exceeding 15%. In contrast, Romania, with a lower level of digital skills (57%), shows an AI adoption rate of only 1.5%. Furthermore, the correlation between machine learning and robotic process automation is 0.878, indicating that these technologies work closely together to optimise industrial and business processes. These findings confirm that digitalisation and robotization levels play a crucial role in the successful integration of AI technologies.

**H3:** The research identifies several barriers in Central and Eastern European (CEE) countries, including insufficient technological infrastructure and a lack of digital skills, as key factors contributing to the low AI adoption rates. Romania (1.5%) and Bulgaria (3.6%) demonstrate minimal AI usage, aligning with their lower levels of digital skills and underdeveloped infrastructure. Similarly, Hungary's AI adoption rate is only 3.7%, which can be attributed to similar challenges. These results underscore the need for technological development and digital education initiatives to support progress in these regions.

This study provides a comprehensive statistical analysis of the use of artificial intelligence technologies in different industries in the European Union, with a special focus on the business sector. The analysis is based on the 2023 survey *"ICT usage and e-commerce in enterprises"*, in which 150,400 EU companies participated. A major novelty of the research is that it examines the correlations between different AI technologies, including machine learning, robotic process automation, text mining and speech recognition technologies. The analysis uses several statistical methods, such as correlation analysis, factor analysis and principal component analysis, to explore in detail the relationships, synergies and possible redundancies between technologies.

The findings of the study contribute directly to answering the three main research questions. Regarding RQ1, multivariate statistical methods confirmed that AI adoption varies significantly across countries depending on their level of economic development and digital infrastructure. For RQ2, the results highlight that the degree of digitalisation and the presence of robotization technologies are closely related to AI integration, with strong correlations observed between key technologies. In relation to RQ3, structural barriers in CEE countries were identified and validated, including underdeveloped digital ecosystems and limited digital competencies.

The results show that certain AI technologies, such as machine learning and robotic process automation, are closely linked, which could lead to significant efficiency gains. The research emphasises the role of the determinant of the correlation matrix, which reveals multicollinearity between variables. The factor structures defined by the Kaiser–Meyer–Olkin test and the Bartlett test allow for a more precise analysis of the relationships between variables. These results can help to plan the successful integration of AI technologies in industry and services.

The research also highlights the significant differences in the adoption of AI technologies across EU countries. Economically developed countries such as Denmark, Finland and Luxembourg are significantly ahead in the adoption of AI, while less developed regions such as Romania face significant challenges in terms of technological infrastructure and digital skills. Multivariate statistical analyses, including PCA and cluster analysis, provide deeper insights into patterns of AI adoption and the factors influencing the technological development of each country.

The cluster analysis identifies three main groups based on the application of AI technologies. The first group includes countries like Austria, Belgium, Denmark, and Finland, which have exceptionally advanced technological infrastructure. The second group, which includes Hungary, Poland, and France, demonstrates a moderate level of AI adoption but faces several challenges in the widespread implementation of AI technologies. The third group is comprised solely of Slovenia, which stands out significantly from the other countries in terms of AI technology application.

Additionally, the multidimensional scaling visualizes the differences between countries based on their level of AI integration. The $R^2$ value of the MDS model suggests that the dimensions represented accurately reflect the variations between countries. The x-axis captures the technological advancement of countries, while the y-axis represents their economic development and the pace of AI integration.

In summary, the research provides valuable insights into the prevalence and usage of AI technologies across the European Union and highlights the relationships between different technological factors. These findings can contribute to the development of future AI strategies, particularly in supporting technological advancement in less-developed regions. The use of statistical methods, such as reducing variables to six key indicators and applying principal component analysis, offers a strong foundation for understanding the effective application of AI technologies in both industrial and service sectors.

Nevertheless, some limitations of the study should be acknowledged. First, the data used were limited to a single Eurostat survey, which may not fully capture the dynamic and sector-specific nature of AI adoption, especially in emerging industries. Second, the scope of variables was constrained by the availability of harmonised EU-level data, and therefore may not reflect all relevant dimensions of AI integration – such as regulatory environment, organisational readiness, or sectoral innovation capacity. Third, the analysis focused on enterprise-level responses and did not account for consumer-side factors or informal technological diffusion. Finally, the statistical associations identified do not imply causality and may be influenced by unobserved contextual variables, such as national policy differences or cultural attitudes towards automation. These limitations suggest that caution should be shown towards generalising the results beyond the scope of the selected dataset and emphasise the need for further longitudinal and mixed-method research.

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