sciendo

Mapping AI Adoption across Europe: A Cluster Analysis of National Responsibility

Eduard-Mihai MANTA
Bucharest University of Economic Studies, Bucharest, Romania
eduard.manta@csie.ase.ro

Maria Cristina GEAMBASU*
Bucharest University of Economic Studies, Bucharest, Romania
**Corresponding author, geambasumaria14@stud.ase.ro*

Ioana BIRLAN
Bucharest University of Economic Studies, Bucharest, Romania
birlanioana19@csie.ase.ro

Abstract. *This paper explores the responsibility of European countries in adopting artificial intelligence (AI) through a cluster analysis approach. Using hierarchical clustering (Ward's method) and K-means clustering, distinct groupings of nations are identified based on their level of AI adoption. The analysis reveals key performance poles, highlighting countries leading to AI adoption and those facing significant challenges due to digital infrastructure, public trust, and policy frameworks. The study relies on data from Eurobarometer 95.2 (2021), incorporating variables related to digital literacy, AI perception, internet usage, and technological infrastructure. Results show clear regional disparities: Northern and Western European countries demonstrate higher AI adoption responsibility, benefiting from strong policies and digital ecosystems. In contrast, Southern and Eastern European nations face obstacles such as limited infrastructure and weaker regulatory frameworks. The findings contribute to a deeper understanding of AI adoption dynamics, revealing structural differences between clusters and offering insights into the key drivers of AI integration. By applying unsupervised machine learning techniques, this research underscores the need for tailored policy interventions to bridge the AI adoption gap. The results provide a foundation for designing targeted strategies that promote AI integration across different national contexts, ensuring more inclusive and sustainable technological development.*

Keywords: Cluster Analysis, Artificial Intelligence Adoption, Hierarchical Clustering, K-Means Clustering, European Countries.

Introduction

As Europe forges ahead with its digital transformation, adopting and embedding artificial intelligence (AI) technologies is increasingly envisaged as lining up at the forefront of this transformation, with potentially broad-based economic, social, and policy implications. However, whilst AI holds considerable promise for growth, innovation, and quality of life, the speed and efficiency of adoption vary significantly between EU member states. How these differences translate into varying attitudes toward technology and the impact of both on long-term public policy are critical to understanding the pursuit of targeted policies that promote inclusive and sustainable technological innovation.

Europe has historically had a varied capacity for using technological advances and integration. The rate of AI adoption is heavily influenced by factors such as technological infrastructure, digital literacy, public attitudes toward technology, and regulatory environments.

DOI: 10.2478/picbe-2025-0119

Prior research has noted stark divides between Northern and Western Europe, defined by strong digital ecosystems, and Southern and Eastern Europe, where infrastructural and regulatory challenges remain.

This study employs advanced clustering methodologies to explore the accountability and preparedness of European countries for adopting AI technologies. Using hierarchical clustering (Ward's method) and K-means clustering methods, the study reveals that distinct groupings can explain countries according to their AI adoption profiles based on the indicators of digital literacy, technological infrastructure, attitude toward AI, use of the internet, and overall digital competence. Using data from Eurobarometer 95.2 (2021) provided a broader analysis that includes visualizations illustrating structural differences and similarities across countries.

Based on this background, this paper detects differentiated clusters of countries with differential readiness for AI adoption in Europe. In this context, the main research question of this study is: "In what clusters do European countries group according to their responsibility as well as readiness for AI adoption, and what are the relevant ramifications of these clusters for policy-making towards inclusive technological development?" By employing this focused approach, the goal is to highlight structural differences and refine the strategies needed to close the gap in AI adoption on the continent.

The paper is structured as follows: the next section reviews relevant literature and theoretical foundations and the methodology detailing the clustering approaches. Subsequently, the results are presented and discussed, highlighting significant patterns and implications. Finally, conclusions and policy recommendations based on these findings are provided.

Literature review

Artificial Intelligence (AI) is making its way into Europe. It thus has become a fertile ground for academic and policy-related work, with many studies devoted to understanding AI drivers, barriers, and enablers at the national and regional levels. This study applies cluster analysis to European countries according to their AI adoption responsibility. It provides a new perspective on digital transformation while exposing structural differences and potential pathways for targeted policies. This literature review contextualizes the paper's contributions by synthesizing previous research on AI adoption, clustering methodologies, and European digital policies.

The adoption of AI varies widely between European countries due to differences in all technological infrastructure, regulatory environments, the public perception of AI, and levels of investment. Countries like Sweden, Denmark, and the Netherlands are usually seen as digital front-runners, enjoying favourable digital ecosystems, supportive governments, and high digital literacy (Bughin et al., 2019; European Commission, 2020). In contrast, Southern and Eastern European countries experience structural issues, such as a lack of infrastructure and slower adaptation of regulation (OECD, 2021). However, these disparities highlight the need for targeted policies to close the gap in AI adoption.

Clustering techniques such as hierarchical clustering and K-means clustering have been used to identify patterns in progress in technology concerning social sciences and economics. These methods characterize groups of countries that gather similar trends concerning the adoption of AI, enabling comparative policy analysis (Everitt et al., 2011). Past research that has adopted types of cluster analysis to evaluate differing digital transformation trends has shown that digital skills, economic development, and policy frameworks differentiate best between the analyzed clusters (Liao, 2019; Wirtz et al., 2020). These techniques allow researchers to draw lessons about how national characteristics influence the embrace of AI.

Digital infrastructure is a key driver of AI adoption, determining the availability and efficiency of AI services. According to research, broadband penetration, cloud computing, and data storage are critical prerequisites for AI readiness (McKinsey Global Institute, 2018; Brynjolfsson & McAfee, 2017). Traditionally, Northern and Western European nations perform very highly on digital infrastructure: almost 90% penetration of high-speed internet (ITU, 2021), while Eastern European nations often posted lower connectivity rates. Previous studies in the digital economy have shown that infrastructure matters in the emergence of AI clusters.

Public attitudes toward AI affect adoption rates, and trust in AI systems varies widely in Europe. Research indicates that countries with top digital literacy generally accept AI technologies (Ribeiro-Navarrete et al., 2021). Studies like Eurobarometer 95.2 (2021) show that trust in AI is highest in Nordic nations, with perceptions of AI as a tool of efficiency and innovation. Lower digital literacy in other countries can lead to scepticism or fears of job displacement and ethical implications (Hagendorff, 2020). This difference in AI perception seems to be part of the clustering of nations we observe.

Government policies and regulatory frameworks drive national patterns of AI adoption. The European Union (EU) has unveiled several policy initiatives to create a conducive environment for AI integration, such as the European AI Strategy and the Digital Compass 2030 framework (European Commission, 2021). Nonetheless, implementing these policies is inconsistent among member states, resulting in varying degrees of AI readiness (Veale & Binns, 2017). France and Germany are examples of countries leading the way with proactive AI policies through national AI strategies that propel innovation and investment (AI Watch, 2020). Conversely, countries with less robust regulatory regimes tend to see slower gains in AI adoption.

To a large extent, the responsibility for AI adoption can also be attributed to the nation's economic strength and industrial competitiveness. Richer countries invest more in AI research and development, showing adoption rates (Manyika et al., 2017). According to a recent World Economic Forum (2020) study, a strong relationship exists between GDP per capita and AI readiness, as advanced economies focus on AI-based automation in key sectors. Countries with lower GDP–PPP per capita are often too impoverished to invest in AI capability development at a competitive rate, thus importing most of the AI systems used in the country 7,8.

The availability of skilled professionals is a fundamental enabler of AI adoption. Countries promoting STEM (Science, Technology, Engineering and Mathematics) related capabilities in their education system have more prepared labour markets for AI (Frey & Osborne, 2017). Countries that have invested in higher AI education and training programs have been shown to adopt AI at higher rates, such as Finland and Estonia (Pajarinen et al., 2019). In contrast, countries with skills gaps cannot adopt AI technologies due to the difficulty businesses experience in hiring AI talent (Chui et al., 2018).

Across diverse European territories, ethical issues such as bias, transparency, and accountability influence the uptake of AI. The call for frameworks has been reinforced by studies highlighting the significance of ethical AI, which fosters fairness and mitigates bias (Floridi & Cowls, 2019). High AI ethics regulations, such as those of Germany and the Netherlands, correlate with a more favourable attitude toward AI systems (Jobin et al., 2019). On the other hand, countries with less mature ethical guidelines will likely encounter pushback from the public and policymakers on deploying AI solutions.

In a first approach, the AI Watch (2021) surveyed EU member states regarding AI readiness, enabling assistance to identify where the socio-economic divide remains between the digital front-runner and laggards comparatively across AI-o LED countries. For instance, a study by the OECD (2020) examining the implications of AI-driven disruption for labour markets also frames the need for policy interventions to enable inclusive growth in the context of AI. These studies are a reference point for this paper, which uses clustering methods to cluster countries in groups based on the level of responsibility concerning the adoption of AI.

Considering these differences in the adoption of AI among different target groups, we foresaw that future studies should explore ways to narrow the digital divide. To ensure that AI is apportioned fairly to all countries, policymakers should devise interventions to target them according to their unique requirements. With emphasis on investment in digital skills training, infrastructure development, and regulatory harmonization, fostering a more inclusive AI landscape in Europe will be the key (Bughin et al., 2019). Furthermore, as global leaders unite to share supplications, cross-border partnerships and thought-sharing will spur AI adoption and integration within less developed areas.

Data and Methodology

Dataset

The data for this analysis was extracted from Eurobarometer 95.2 (2021) and was oriented toward indicators of AI adoption responsibility across European states. Data is organized with ten pillars: Internet usage, Impact of technology, Efficiency and position of the population in technology, Digital competence, Trust in online information, Robotics and artificial intelligence, population's comfort in accessing advanced technology, Access to and use of medical data, Online security, Satisfaction with living conditions. These variables are a comprehensive package that allows a logical understanding of structural patterns of AI adaptation within the states.

The study covers 28 European countries: France, Belgium, Netherlands, Germany, Italy, Luxembourg, Denmark, Ireland, United Kingdom, Greece, Spain, Portugal, Finland, Sweden, Austria, Cyprus, Czechia, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Slovakia, Slovenia, Bulgaria, Romania, and Croatia. SPSS was employed for basic descriptive data analyses, and R was used for statistical modelling.

PCA and PLS methodology

To quantify the responsibilities of European countries in AI adoption, Principal Component Analysis (PCA) and Partial Least Squares (PLS) were employed to synthesize a comprehensive measure based on the ten key pillars previously listed.

A popular statistical method for reducing dimensionality in data analysis and machine learning is PCA. Its goal is to convert a set of data into a new coordinate system in which the first coordinates (also known as primary components) have the largest variance by any data projection, the second coordinate has the second-greatest variation, and so on.

Principal components analysis has the following stages:

1. Data standardization
2. Calculation and interpretation of Covariance Matrix
3. Calculating eigenvalues and vectors to determine principal components
4. Calculating the rotated matrix to project the original data into the dimensionality of the new components
5. Calculation of the index based on the formula:

   $$I = w1 * PC1 + w2 * PC2 + ... + wk * PCk,$$

   Where w1, w2, ..., wk are the weights of the eigenvalues; PC1, PC2, ..., PCk are the principal component scores.

By extracting a set of components (latent factors) for both X and Y, PLS, a statistical modelling technique primarily used for multivariate regression and structural analysis of latent relationships (SEM), seeks to maximize the explained variance of the dependent variables (Y) by the independent variables (X).

The stages PLS analysis are:

1. Calculation of weight vectors
2. Calculation of component scores
3. Calculation of correlations between original data and new components
4. Updating the X and Y matrices
5. Calculating the index

Similar findings were obtained by both PCA and PLS. The target areas for the first component include digital accessibility and data privacy. For the second component, AI scepticism is connected to low trust in online information. Component three reflects digital literacy and ease with AI support. Component 4 focuses on the role of social trust and AI news. Component 5 It exhibits a sphere of careful AI adoption, with worries about things like online shopping and AI administration. But, however, Component 6 will focus on IT security. Component 7 suggests growing openness to AI solutions, while Component 8 points to resistance in certain contexts.

It is important to note that the synthetic indices for AI adoption responsibility were constructed in a separate yet unpublished study. This paper exclusively focuses on applying cluster analysis to identify performance poles and regional disparities in AI adoption.

Cluster analysis

Clustering analysis is a method of unsupervised learning that seeks to organize a set of objects in groups, known as clusters, so that objects in the same cluster are more like each other than those in different clusters. Cluster analysis seeks to discover previously unknown structures or patterns in the available data. It is employed widely across numerous domains, such as advertising, biology, pattern recognition, medical imaging, and community data analysis.

For the cluster analysis, we executed two styles of clustering:

1. Hierarchical (Ward) - Is a hierarchical cluster analysis method that minimizes the in-cluster variance between the points. Ward’s method is preferred because it identifies excellent clusters. Euclidean distance formula:

$$\Delta E = \frac{|C_i| * |C_j|}{|C_i| + |C_j|} \sum_{x \in (C_i \cup C_j)} (x - \bar{x})^2$$

   Where, $|C_i|, |C_j|$ – represent cluster dimension; $\bar{x} -$ cluster mean C_i și C_j;

2. K-means is an unsupervised learning algorithm that models a dataset into K clusters. Every cluster is represented by its centroid and its centre, and each data point is assigned to the nearest one. The algorithm tries to minimize the distances of the observation points from respective cluster centroids. These distances are calculated with the Euclidean distance to point x and centroids k, with the formula:

$$d(x_i, \mu_j) = \sqrt{\sum_{l=1}^{p} (x_{il} - \mu_{jl})^2}$$

Where x_i – the i-th data point; μ_j – the centroid of cluster j; p - is the number of variables;
The centroid is updated using the formula:

$$\mu_j = \frac{1}{|C_j|}\sum x_i$$

Where μ_j – is the new centroid of cluster j; $|C_j|$ - the number of data points in cluster j; $x_i \in C_j$ – are the data points in cluster j;

Results and discussions

Cluster analysis based on PCA index

Based on the AI adoption PCA index, calculated in another unpublished paper, and its principal components, Figure 1 was computed. A scatter plot of countries based on the two principal components was used to visualize the results further.

Specifically, in component 1, the most important variable is "Exposure to news related to artificial intelligence in the last 12 months", and in the second component, "The population feels comfortable being assisted by a robot at work". A breakdown of the chart lays out the next insights: Sweden seems to face low exposure in terms of news related to artificial intelligence, yet the population has extremely low reluctance at work to use robots, which shows a very high acceptance of robotics. Romania shows little news exposure to Artificial Intelligence stories and almost no interest in the non-business use of robots (no acceptance of robotic technologies). And Denmark, like Sweden, has little news exposure to artificial intelligence and an elevated comfort level among its population of working with robots. Italy is heavily exposed to news about artificial intelligence, yet sceptic regarding using robots at work.

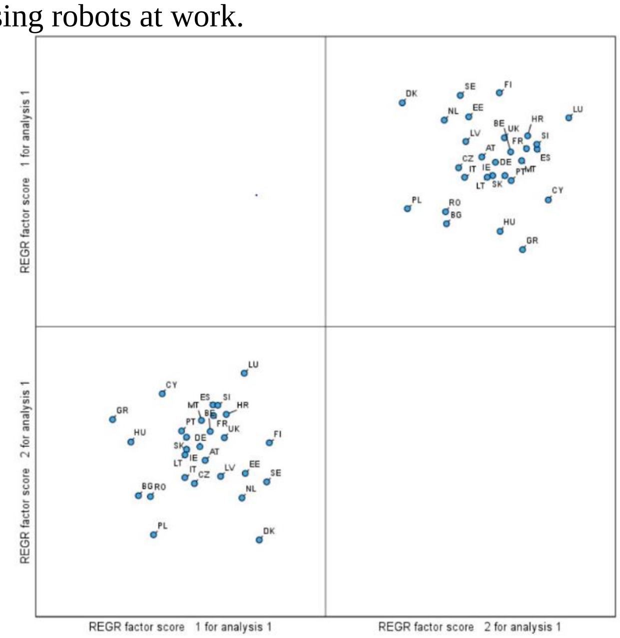

Figure 1. The position of countries based on the first two principal components of PCA

Source: Authors' own research results.

The hierarchical clustering creates 5 clusters comprising the 28 observations, as illustrated in Figure 2. The observations were split into 5 clusters through the Ward hierarchical method. The first cluster is Cyprus, Greece , and Hungary. The second cluster is Romania, Bulgaria, and Poland. The third group comprises Portugal, Slovakia, Ireland, Lithuania, Germany, Austria, Latvia, Italy, and Czechia. The fourth cluster comprises Luxembourg, Croatia, France, Spain, Slovenia, the UK, Belgium, and Malta. Cluster 5: Denmark, Sweden, Finland, the Netherlands, Sweden, and Estonia.

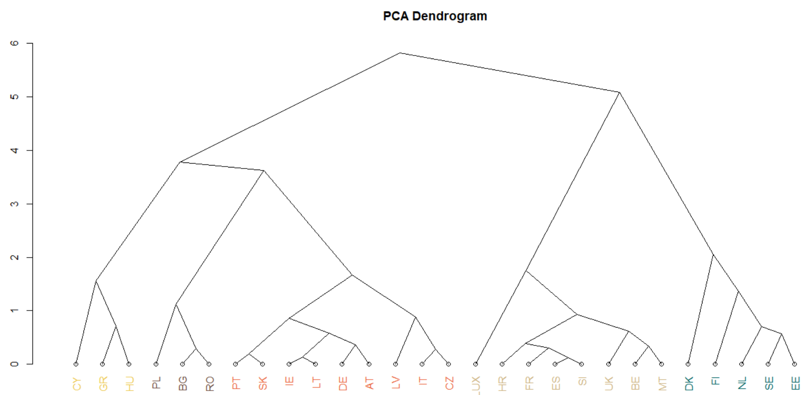

Figure 2. PCA Dendogram

Source: Authors' own research results.

The clustering looks similar using K-means, but there is one change: Latvia migrates from cluster 3 to cluster 5.

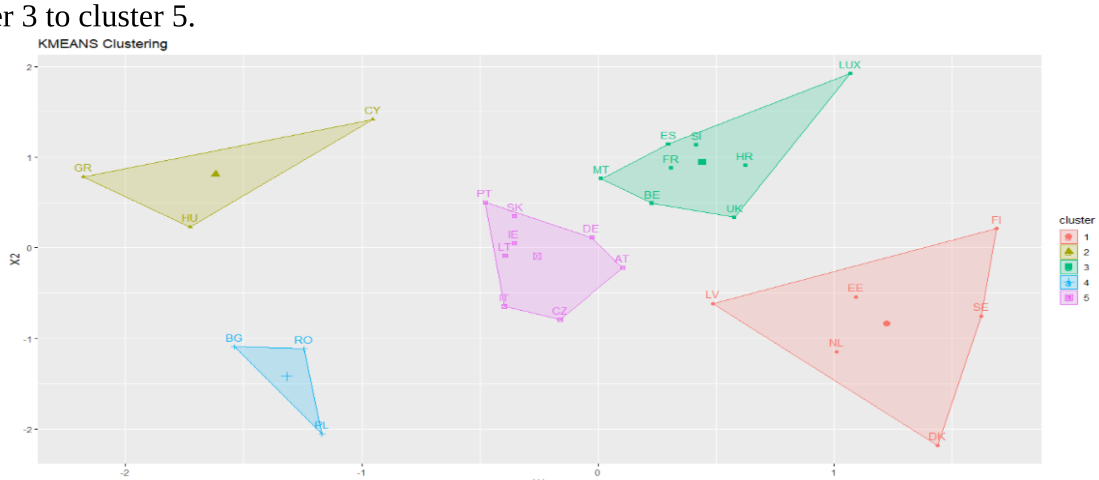

Figure 3. K-mean algorithm PCA

Source: Authors' own research results.

The first group includes Cyprus, Greece, and Hungary, countries struggling to adopt AI and digital technologies. Internet use is limited, and the effects of technology on the economy and social life are perceived as moderate. Confidence and competence in new technologies and digital skills are low. These countries are also less exposed to information about robots and AI, and public opinion about these technologies is neutral or negative. Economic woes, including Greece's debt crisis and Hungary's sluggish recovery from recession, have constrained public and private investment in A.I. and broadband infrastructure. Digital accessibility is low, and in some industries (tourism: Cyprus, Greece, and manufacturing: Hungary), there hasn't yet been a focus on integration of AI. Scepticism on the cultural side becomes due to job security concerns and a lack of exposure to AI-related advances. Shifting government priorities, bureaucratic bottlenecks, or inconsistent digital policies have further delayed AI adoption at scale politically: Digital transformation in the government has been a slow process.

Adopting AI and digital technologies is the most difficult task for Romania, Bulgaria, and Poland. Daily internet usage is low, and the perceived benefit of the technology to the economy and social life is small. The trust in recent technologies and digital skills is at its bare minimum. Many of these countries are not exposed to information about robots and AI and see little to no use of robots in real life. The fear that robots will replace jobs dominates the perspective, and the benefits of robotics are only marginally acknowledged.

The poorest performance may be seen in this cluster due to lower GDP per capita levels, poorly developed broadband infrastructure, and a large share of rural population without access to the internet remain major challenges. However, AI and automation is still a relatively unused part of the industries that there are. These countries have historically not focused on STEM and digital literacy as part of their educational systems, resulting in a population that lacks confidence and competence in AI. The fear of job losses due to automation is a major hurdle, especially in sectors that are dependent on low-wage labour. In terms of digital transformation, this political inertia has created laggards out of these member states when it comes to slow regulatory adaptation and delayed investments in AI infrastructure, even as EU support has grown.

Cluster 3: In countries with high AI and digital adoption, Internet use is moderate to high, and the impact of technology on the economy and social life is seen positively. The intended use of emerging technologies and digital skills is highly mature. These countries show moderate exposure to knowledge about robots and AI and reveal a balanced public opinion about its benefits and risks. Countries such as Portugal, Czechia and Spain see the GDP growth rate and expand investments in broadband and AI infrastructure steadily. Moderate to high internet penetration and a positive outlook on the effect of technology on lives and the economy. Socially, younger populations are generally more digitally capable, while older generations are more doubtful of the benefits of AI. With more news and information about AI available to the public, opinions are starting to balance out. Governments, meanwhile, implement digitalization strategies with the aid of EU funding; however, regulatory frameworks and levels of investment remain acute for Europe compared to the leading AI adopters.

Cluster 4 consists of the countries that are up to speed with AI and digitalization. Internet usage is prevalent, and the positive contribution of technology to the economy and social life is widely acknowledged. Recent technology use and digital skills are very trusted. Citizens in these countries are often in touch with information about robots and AI, and they have a favourable attitude towards the technologies, recognizing their potential for increased efficiency and work security.

These developed countries are characterized by industrialized and service-oriented economies that leverage AI technologies across critical sectors such as manufacturing, finance, and healthcare. Germany, for example, excels in AI-driven manufacturing (Industry 4.0), whereas France and Ireland are focused on fintech and automation. Public confidence in digital technologies is high, underpinned by sophisticated education systems that promote digital skills. National governments have developed AI policies which include the establishment of regulatory frameworks and funding initiatives that drive AI engagement. The data usage of these countries is significant, characterized by a wide range of broadband segments, and the digital change is backed with collaboration between sectors of the public and private.

The leading countries adopting AI and digital technologies are in Cluster 5. Very high daily internet usage and a view that the impact of technology on social life and the economy is extremely positive. We are at the highest level of trust in using recent technologies and digital skills. These countries are leading the way in using technology to enhance quality of life and work efficiency. There is strong public support and general acceptance of robots and AI throughout citizens' daily lives. Denmark, Sweden, Finland, the Netherlands, and Estonia lead the pack in AI adoption, thanks to robust economies, world-class digital infrastructure and high levels of investment in AI research and development. AI is embedded in many facets — in public services, in finance, in healthcare, in automation — which is why they are the most consumptive and frequent users of the Internet on any given day. Estonia's e-Government model, Finland's AI education programs, and Sweden's emphasis on AI ethics are testaments to their forward-thinking leadership. Public trust in technology is at an all-time high, and digital literacy permeates all age demographics. From a political perspective, this includes AI-friendly regulations, clear national strategies, and strong partnerships between government and industry, putting them at the forefront of the world's next wave of digital transformation.

Cluster analysis based on the PLS index

Figure 4 was computed based on the AI adoption PLS index, calculated in another paper that has yet to be published, and its principal components. A scatter plot of countries based on the two principal components was used to visualize the results further.

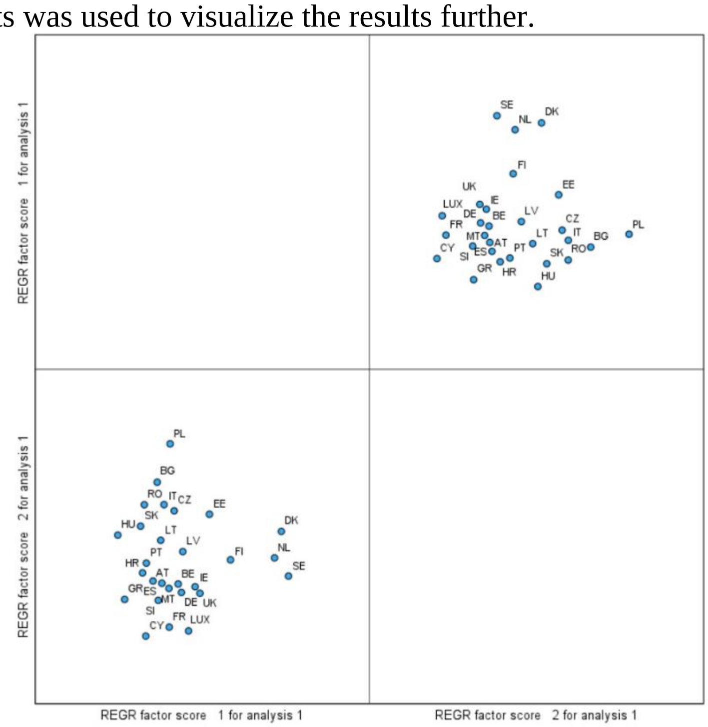

Figure 4. The position of countries based on the first two principal components of PLS

Source: Authors' own research results.

DOI: 10.2478/picbe-2025-0119, pp. 1532-1545, ISSN 2558-9652 |
Proceedings of the 19th International Conference on Business Excellence 2025

Component 1 refers to "Exposure to news related to artificial intelligence in the last 12 months", and its second component focuses on the variable "The population feels comfortable being assisted by a robot at work". It is just one of two elements that illustrate how people deal with AI in various situations, especially their sense of information and comfort with new technology in the workplace.

Hierarchical clustering with Ward's method is a natural follow-up to the analysis. This approach is especially good for reducing the variance inside each cluster and thus allows the detection of groups of countries that present common characteristics. The method focuses on detecting hidden structures and relationships between the states by combining elements into clusters across the observations. It will help to understand how countries are different regarding engagement with AI technologies and their readiness for future developments in this domain.

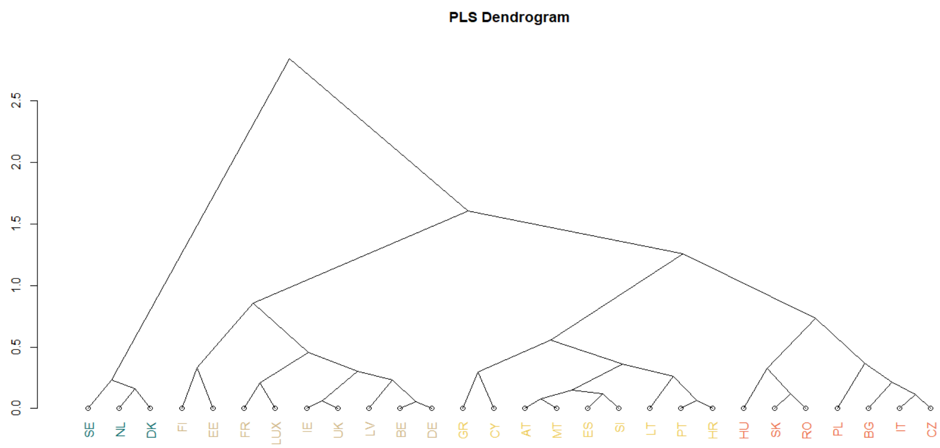

Figure 5. PLS Dendogram

Source: Authors' own research results.

The first group consists of Sweden, the Netherlands, and Denmark, which can be seen as leaders in Artificial Intelligence adoption. The second group comprises Finland, Estonia, France, Luxembourg, Ireland, the United Kingdom, Belgium, and Germany. The third cluster includes Greece, Cyprus, Austria, Malta, Spain, Slovenia, Lithuania, Portugal , and Croatia. The fourth cluster comprises Romania, Hungary, Slovakia, Poland, Bulgaria, Italy, and Czechia.

Using the K-means algorithm but assigning the Netherlands, Sweden, Denmark and Finland to the first cluster provides a different clustering. Cluster 2 members are Croatia, Italy, Belgium, Slovenia and Austria. Lithuania, France, Bulgaria, Czechia, Poland, Hungary, Latvia, Romania, and Germany form the third cluster. Spain, Portugal, Cyprus, Luxembourg, Malta, the UK, Ireland, and Greece comprise cluster 4.

The countries in Cluster 1 are known for their advanced digital infrastructure and rapid adoption of new technologies, which can influence their perception and comfort with robots. Therefore, this cluster could be referred to as "Countries with a high level of responsibility in AI adoption". Although there are variations in the level of digital development within cluster 2, the countries generally have good infrastructures and an openness to innovation but with a more cautious approach to implementing robots. For this reason, cluster 2 could be called "Countries with a medium level of responsibility in AI adoption." Cluster 3 includes countries with a low level of AI adoption, which is why it can be called "Countries with a low level of responsibility in AI adoption". Finally, cluster 4 includes countries with an ascending level of responsibility in AI adoption. Therefore, it can be referred to as "Countries with an ascending level of responsibility in AI adoption".

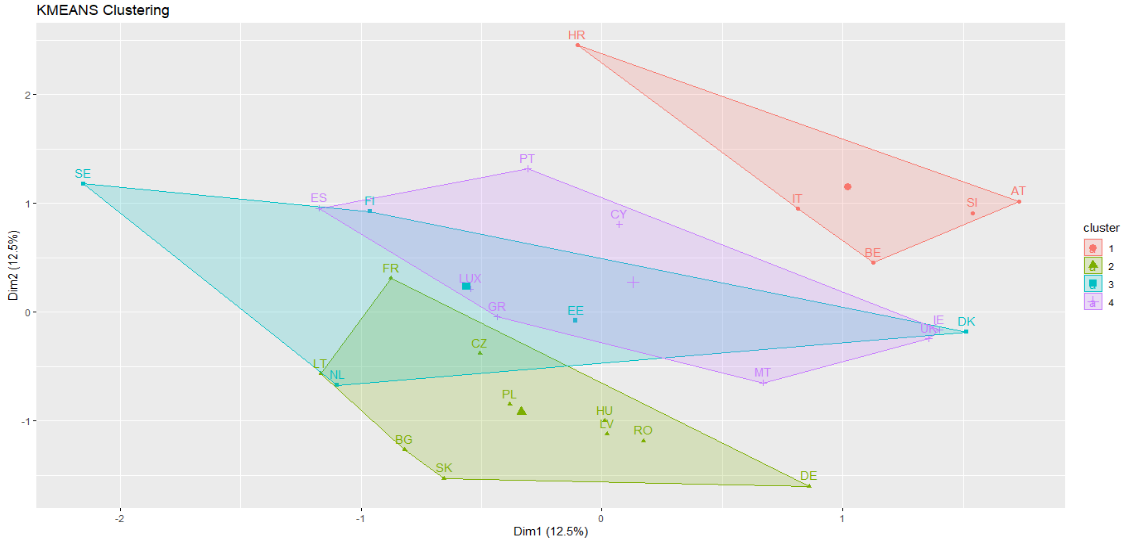

Figure 6. K-mean algorithm PCA

Source: Authors' own research results.

Conclusion and recommendations

This research, based on conclusive analysis of data from Eurobarometer 95.2 (2021) applying hierarchical clustering (Ward's method) and K-means clustering, has offered important reflections on their respective responsibility and readiness for using AI technologies in European states. The resulting clustering painted different groupings of nations, defined by their state of digital infrastructure, levels of public trust, digital capabilities, and the existing policy landscape. Countries in Northern and Western Europe emerged from the analysis as leaders, partly due to their robust digital ecosystems, solid policies and a high level of public acceptance of AI technologies. However, the challenges are significant for Southern and Eastern European countries, arising as much from inadequate infrastructure, lower skill levels and weaker regulations.

Hierarchical clustering revealed five unique clusters, showing considerable regional variation. Northern and Western European countries are best responsible for AI adoption, with Sweden, Denmark, and the Netherlands leading the way based on robust policies and high levels of public trust in technology. Conversely, Southern and Eastern European countries like Romania, Bulgaria, and Poland exhibit broader struggles with infrastructure limitations, public scepticism, and lower baseline levels of digital capability.

K-means clustering also confirmed these results by grouping countries into four clusters and reaffirming the regional characteristics. AI Adoption (AI & Digital Clusters) — Countries in the leading clusters are often backed by strong digital ecosystems, significant government aid, and active AI policies, which lead to high levels of technological absorbance across the economy. On the other hand, countries that fall under lower or emerging degrees of responsibility for AI adoption need an inclusive strategic response focused on infrastructure shortages, digital skills, and regulation augmentation.

The results highlight the need for targeted policy measures to narrow the gaps in the use of AI in European nations. Thus, for inclusive and sustainable growth with technology, the following discussed points require the immediate attention of global policymakers to drive investments towards digital infrastructure and skills development and harmonize the regulatory paradigms across nations. Cross-border partnerships and knowledge transfer initiatives are also highlighted as the strategic way to accelerate AI adoption in areas where it lags.

To expedite AI adoption in cluster 1, these countries must invest significantly in digital infrastructure, notably in expanding broadband and 5G networks into underserved areas. A systematic approach to AI integration will be facilitated by the establishment of unambiguous AI governance frameworks and ethical standards, which will boost public trust. To ensure that the populace is ready for AI-driven sectors, educational reforms should prioritize increasing digital literacy and labour reskilling. Furthermore, encouraging foreign direct investment through tax breaks and financing options for AI research can aid in integrating cutting-edge technology into important economic sectors and progressively overcoming the present reluctance to use AI.

For cluster 2, improving digital infrastructure remains a top priority, since many regions of these countries still lack access to high-speed internet, which creates a huge barrier to AI adoption. Financial incentives should be implemented by governments to help those SMEs hop on the AI bandwagon, thus enabling small businesses to add automation to their digital transformation. Public-awareness campaigns are critical to dispel fears about job displacement and emphasize AI's potential for economic growth. Moreover, research-based approaches ranging from vocational training programmes to more robust STEM education initiatives will equip the workforce with tools for AI-driven industries, facilitating long-term technological advancements in these countries.

In order to maintain and accelerate AI adoption for cluster 3, governments need to place increased emphasis on investing in AI research and development, especially within universities and innovation institutes. Public investment in a transparent, responsible regulatory framework to guide AI technology development will help itself build trust. Increasing the role that A.I. plays in public services like health care, transportation and public safety would also demonstrate the benefits of automation and promote wider acceptance in the population. These countries must position themselves as competitive players in the EU-wide AI stage by attracting resources through ethical practices and compliance with the respective policies in the bloc relevant to AI.

As leaders in AI adoption, Cluster 4 nations need to concentrate on expanding AI integration throughout sectors like manufacturing, banking, and healthcare in order to optimize financial gains. To ensure a coherent European AI policy, strengthening cross-border cooperation inside the EU will improve AI innovation and regulatory coherence. Supporting AI-driven developments in public services would significantly simplify the systems of government, healthcare, and education. Continuous efforts to improve AI rules, ethical AI development, and data privacy must continue to be a top priority to preserve public trust and guarantee that AI adoption is responsible and advantageous for all citizens.

Cluster 5 as global leaders in AI adoption, these countries should maintain this trajectory in AI governance, establishing ethical standards and promoting transparent, bias-free algorithms. Strengthening their competitive advantage through University - Industry partnerships to expand local AI research and innovation ecosystems fund and resource. Financing and resource support for AI startups and SMEs will promote economic growth and maintain technical breakthroughs. Additionally, by luring and keeping the best AI talent with research grants, tax breaks, and laws that support digital nomads, these nations will continue to lead the way in AI and serve as role models for the rest of Europe and beyond.

There are some limitations in this study that future research should overcome. First, the analysis relies on cross-sectional data from the Eurobarometer, restricting the opportunity to analyze dynamic changes within time. We suggest future studies should be longitudinal to identify trends over time and the impact of policy implementation. Moreover, the study is limited to clustering methods, which do not provide signs of causality; more in-depth insights about underlying drivers of AI adoption could be obtained using qualitative methods or econometric modelling. In addition, a larger dataset, incorporating factors like AI investments and workforce quality by skill, could provide more detailed insights into differences between countries.

This study thus provides unique insights into the heterogeneity of AI adoption in Europe, highlighting the need for more discriminative and localized policy responses. Targeted interventions will be necessary to address these gaps and ensure that former sustainable technology development occurs across the continent.

Acknowledgement

This research was conducted within the Business Economics Data Science Lab and supported by the project ASE-RISE – 'Promoting Excellence in Research through Interdisciplinarity, Digitalization, and Open Science Integration to Enhance International Visibility' (CNFIS-FDI-2025-F-0457).

References

AI Watch. (2020). Artificial Intelligence in Europe: Trends and Developments. European Commission.

Brynjolfsson, E., & McAfee, A. (2017). Machine, Platform, Crowd: Harnessing Our Digital Future. W.W. Norton & Company.

Bughin, J., et al. (2019). Tackling Europe's Gap in AI and Digital Transformation. McKinsey & Company.

Chui, M., Manyika, J., & Miremadi, M. (2018). AI Adoption and Workforce Readiness. McKinsey Global Institute.

European Commission. (2021). Europe's Digital Decade: Digital Compass 2030.

European Commission. (2020). The AI Policy Framework in Europe.

Everitt, B., Landau, S., Leese, M., & Stahl, D. (2011). Cluster Analysis (5th ed.). Wiley.

Floridi, L., & Cowls, J. (2019). A Unified Framework of Five AI Ethics Principles. Minds and Machines, 29(4), 563-591.

Frey, C. B., & Osborne, M. (2017). The Future of Employment: How Susceptible are Jobs to Computerization? Technological Forecasting and Social Change, 114, 254-280.

Hagendorff, T. (2020). The Ethics of AI Ethics: An Evaluation of Guidelines. Nature Machine Intelligence, 2(6), 423-429.

ITU. (2021). Measuring Digital Development: Facts and Figures 2021. International Telecommunication Union.

Jobin, A., Ienca, M., & Vayena, E. (2019). The Global Landscape of AI Ethics Guidelines. Nature Machine Intelligence, 1(9), 389-399.

Liao, S. H. (2019). Clustering Analysis in Digital Transformation Research. Journal of Business Research, 101, 145-157.

Manyika, J., et al. (2017). Artificial Intelligence: The Next Digital Frontier? McKinsey Global Institute.
McKinsey Global Institute. (2018). Notes from the AI Frontier: Modeling the Impact of AI on the World Economy.
OECD. (2020). Artificial Intelligence, Digital Transformation and Productivity. Organization for Economic Co-operation and Development.
OECD. (2021). Digital Economy Outlook 2021. Organization for Economic Co-operation and Development.
Pajarinen, M., Rouvinen, P., & Ylhäinen, I. (2019). AI and Work: Evidence from the Nordic Countries. ETLA Working Papers.
Ribeiro-Navarrete, S., Saura, J. R., & Palacios-Marqués, D. (2021). Towards a New Era of Mass Data Collection: Assessing Digitalization through Cluster Analysis. Journal of Innovation & Knowledge, 6(1), 15-23.
Veale, M., & Binns, R. (2017). Fairness and Accountability Design Needs for Algorithmic Support in High-Stakes Public Sector Decision-Making. Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems, 1-14.
Wirtz, B. W., Weyerer, J. C., & Geyer, C. (2020). Artificial Intelligence and the Public Sector—Applications and Challenges. International Journal of Public Administration, 43(7), 596-616.
World Economic Forum. (2020). The Future of Jobs Report 2020. World Economic Forum.