

EU-27 AI Readiness. A Cluster Analysis

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Abstract

Artificial Intelligence continues to advance very quickly, and its integration into business models is considered absolutely necessary and imminent for business continuity. However, there are a number of challenges regarding the AI development and implementation process related to aspects such as costs, infrastructure, human capital, regulation, security, and countries that manage to respond efficiently and inclusively to these challenges have a high potential to gain competitive advantages. Thus, the objectives of this paper is to analyze the grouping of EU-27 Member States into performance clusters from an AI readiness point of view, and at the same time to analyze patterns of convergence/divergence over time. The research methodology is based on descriptive analysis, cluster analysis and critical comparative analysis. The research results show that the highest AI Readiness is in countries from Western and Northern Europe, with only Denmark, France, Germany and the Netherlands recording a constant evolution. The results also show that the worst performers are Romania and Croatia, and that there is a tendency for certain states to converge towards the most developed cluster.

Keywords

Artificial Intelligence; European countries; cluster convergence

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Introduction

Artificial Intelligence (AI) is currently at the center of future innovation strategies in global industry, Zhang and Li (2026) showing that AI can serve as a catalyst for high-quality innovation in businesses. AI has the potential to enable new business models and drive business excellence, but sustainable and inclusive implementation requires significant investments in infrastructure, human capital skills development, and according to Pan et al. (2026), government commitment to innovation.

AI is developing very fast and is being implemented in a very diverse range of fields, stimulating innovation and improving operational efficiency. According to the AI Index 2025 Annual Report by Stanford University, AI business usage increased from 55% in 2023 to 78% in 2024 (Maslej et al., 2025). AI adoption is also considered a key factor for the success of firms' digital transformation (Bai and Cui, 2026).

Thus, it becomes obvious that in order to have sustained competitiveness, it is necessary for national public and private organizations to adopt AI. For AI adoption to be effective and efficient, a high level of preparedness is necessary, covering aspects such as AI infrastructure, AI policies, development and diffusion capacity or resilience.

In this context, the paper attempts to answer the following questions:

Q1: How are the EU-27 Member States grouped in terms of AI readiness?

Q2: Are there patterns of convergence/divergence between these states over time?

Thus, the paper attempts to contribute to the scientific literature by expanding the empirical framework for analyzing disparities between EU-27 Member States in terms of AI readiness, through a comparative approach based on a multidimensional index.

1. Review of the scientific literature

The specialized literature studying AI is in an accelerated development, with researchers analyzing various aspects, such as the role of AI in certain sectors of activity, benefits, implications, enablers, and associated challenges.

The essential role of AI adoption is highlighted in many industries: hospitality (Alam et al., 2025), urban sustainable development (Liu et al., 2026), healthcare (Kanyal & Mehta, 2026), or construction (Zuofa & Ochieng, 2026).

Regarding benefits, Cooper (2025) conducted a study at the level of Irish small-to-medium-sized enterprises and demonstrated that AI has a high potential to support new product development, but currently the level of readiness of these companies for adopting AI is low. Another benefit is illustrated by Meng et al. (2026), who emphasize its role in strengthening the resilience of the financial system, while Li and Ding (2026) concluded that AI implementation has the potential to reduce corporate default risk, and Emin and Emin (2025) note the ability of AI adoption to reduce credit risk.

Also related to the positive effects of AI, Singh and Mishra (2025) demonstrate the positive link with business sustainability, Kulkarni et al. (2024) argue that AI readiness has a direct impact on social sustainability, and Li (2026) illustrates that AI adoption improves companies' ESG performance.

Testa et al. (2026) show that AI readiness is a booster for increasing career adaptability, and Wang et al. (2023) noted that teachers with high levels of AI readiness have high capacity for innovation and professional satisfaction.

On the other hand, Pramanik, Jana and Ghosh (2024) demonstrated that enablers of AI readiness in business are different in developed and developing countries, while also indicating certain common factors, including internet infrastructure. Another factor that stimulates AI adoption is highlighted by Lada et al. (2023), namely the top management commitment. The role of top management in supporting AI adoption is also indicated by Gupta et al. (2022), who show that financial readiness has also a positive impact. Further, Mikalef et al. (2022) discuss the role of the state in the development of AI capabilities, highlighting, among other things, the importance of government incentives and regulatory support.

In terms of challenges, Hameed et al. (2026) emphasize the extremely important role of trust in AI implementation, and Schäfer, Leutheuser and Voigt (2026) discuss the factors that support this trust, their results showing that trust in AI depends, among others, on transparency, digital literacy or partnerships. Related to this aspect, Darban et al., (2024) argue that the attitude towards adopting AI solutions depends on age, education and labor market status.

Because measuring the level of development from an AI perspective is very important because it provides essential information regarding the level of competitiveness and the gaps between organizations, Holmström (2022) proposes a framework for characterizing a firm's AI readiness, focused on 4 basic dimensions: technologies, activities, boundaries and objectives.

As we can see, the specialized literature on AI is very diverse, analyzing many specific aspects of it, which have aggregate macroeconomic effects, influencing productivity and implicitly competitiveness at the national level.

2. Research methodology

The applied research methodology consists of descriptive analysis, cluster analysis and critical comparative analysis.

To see how the EU-27 Member States (cases) are divided in terms of AI Readiness, the standardized total scores (using Z-score) of the Government AI Readiness Index for each year from 2020 to 2025 were used. The initial scores were obtained from the Government AI Readiness Index reports produced by Oxford Insights.

For each country i , the following vector is constructed:

$$V_i = (Z_{i,2020}, Z_{i,2021}, Z_{i,2022}, Z_{i,2023}, Z_{i,2024}, Z_{i,2025}) \quad (1)$$

where:

$Z_{i,year}$ represents the standardized total AI Readiness Index scores for country i

These vectors were used as input in the *k-means* method to determine cluster centers and cluster membership. Thus, the states are grouped according to similar profiles.

To determine the optimal number of clusters, the Hierarchical Cluster Analysis (Ward's method and Squared Euclidian distance as a measure) was initially used.

To identify examples of convergence/divergence between states, the same *k-means* clustering method and the same standardized data were used, but the convergence clusters were composed for each year separately (matching clusters based on centroid ordering).

The cluster analysis was performed using IBM SPSS software.

3. Results and discussion

The first step in the cluster analysis was to determine the optimal number of clusters for grouping the selected cases. Based on Hierarchical Cluster Analysis results (Figure no. 1), a number of 3 distinct clusters were chosen.

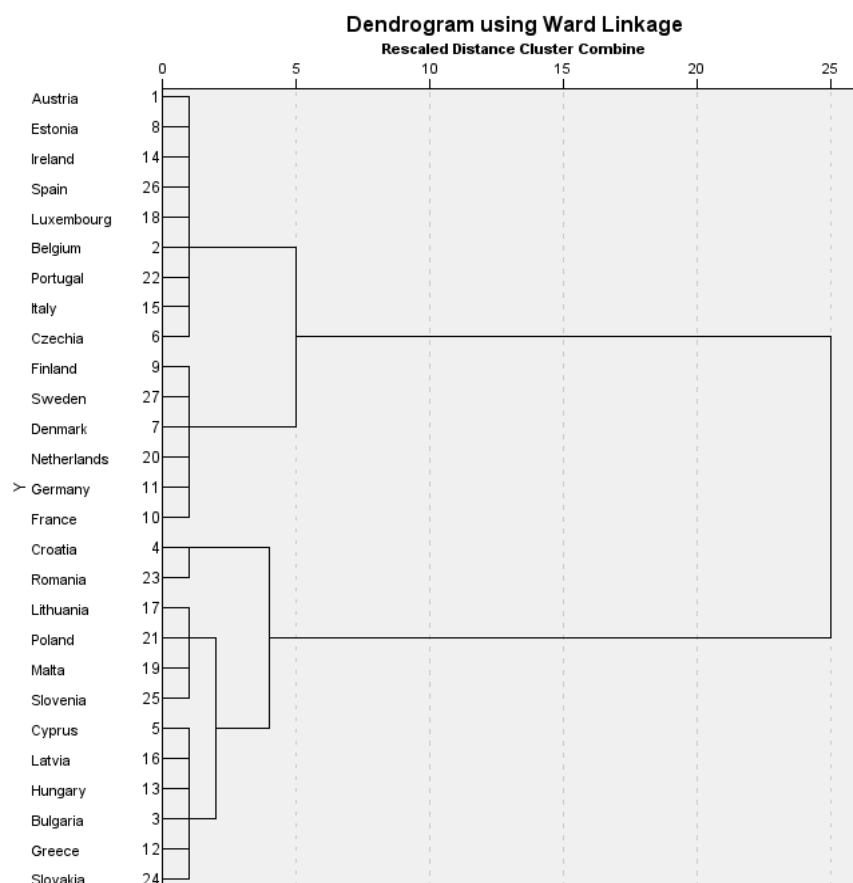


Figure no. 1. Hierarchical Cluster Analysis results

Source: made by the author

After establishing the number of clusters, the *k-means* analysis was performed. Table no. 1 presents the results of the ANOVA analysis, which highlights that the included variables contribute significantly to the differentiation of the clusters.

Table no. 1. ANOVA results

	Cluster		Error			
	Mean Square	df	Mean Square	df	F	Sig.
Zscore(Y2020)	10.778	2	.185	24	58.198	<.001
Zscore(Y2021)	10.601	2	.200	24	53.018	<.001
Zscore(Y2022)	10.308	2	.224	24	45.955	<.001
Zscore(Y2023)	10.557	2	.204	24	51.858	<.001
Zscore(Y2024)	10.431	2	.214	24	48.719	<.001
Zscore(Y2025)	9.086	2	.326	24	27.856	<.001

Source: made by the author

Furthermore, the final cluster centers results for the aggregate analysis (Table no. 2) show that the states in Cluster 1 register a high level in terms of the AI Readiness Index during the analyzed period, with above-average performance and moderate variation. On the other hand, Cluster 2 presents exclusively significant, relatively constant negative values, indicating that it comprises countries with a low level of AI readiness (below average), as well as a lack of significant progress in the period considered.

The third cluster is located between the other two in terms of AI Readiness. The Final Cluster Centers values are close to the average and are relatively stable, highlighting moderate development and prospects of convergence towards the states in Cluster 1.

Table no. 3 presents the Final Cluster Centers for individual cluster analysis for each year from 2020 to 2025.

Table no. 2. Final Cluster Centers for aggregate analysis

	Cluster		
	1	2	3
Zscore(Y2020)	1.04177	-1.21521	-.19113
Zscore(Y2021)	1.06095	-1.15259	-.25414
Zscore(Y2022)	.95472	-1.27990	-.05879
Zscore(Y2023)	1.01184	-1.23384	-.14815
Zscore(Y2024)	.93852	-1.31199	-.02013
Zscore(Y2025)	.84029	-1.25892	-.04096

Source: made by the author

Table no. 3. Final Cluster Centers for annual analysis

	Cluster		
	1	2	3
Zscore(Y2020)	1.27985	-1.13902	.11747
Zscore(Y2021)	1.26735	-1.67132	-.32030
Zscore(Y2022)	.75159	-1.91052	-.61581
Zscore(Y2023)	.94914	-2.11957	-.44296
Zscore(Y2024)	.78769	-1.64162	-.49569
Zscore(Y2025)	1.40166	-1.25892	0.12028

Source: made by the author

The detailed structure of each cluster formed based on aggregated data from the period 2020 - 2025, as well as that of the resulting clusters based on data from each year is presented in Table no. 4.

Table no. 4. Cluster membership

	2020-2025	2020	2021	2022	2023	2024	2025
Country	Cluster						
Austria	1	3	3	1	1	1	3
Belgium	3	3	3	1	3	1	3
Bulgaria	2	2	3	3	3	2	2
Croatia	2	2	2	2	2	2	2
Cyprus	2	2	3	3	3	3	2
Czechia	3	3	3	1	3	1	3
Denmark	1	1	1	1	1	1	1
Estonia	1	3	3	1	1	1	3
Finland	1	1	1	1	1	1	3
France	1	1	1	1	1	1	1
Germany	1	1	1	1	1	1	1
Greece	2	2	2	3	3	2	2
Hungary	3	2	3	3	3	3	3
Ireland	1	3	1	1	1	1	3
Italy	3	3	3	1	3	1	3
Latvia	2	2	3	3	3	3	2
Lithuania	3	3	3	3	3	3	3
Luxembourg	1	1	1	1	1	1	3
Malta	3	3	3	3	3	3	3
Netherlands	1	1	1	1	1	1	1
Poland	3	3	3	3	3	3	3
Portugal	3	3	3	1	1	1	3
Romania	2	2	2	2	2	2	2
Slovakia	2	2	3	2	3	3	2
Slovenia	3	2	3	3	3	3	3
Spain	3	3	3	1	3	3	1
Sweden	1	1	1	1	1	1	3

Source: made by the author

As we can see from global clustering, Cluster 1 includes exclusively countries from Western and Northern Europe, while Cluster 2 (with the worst performance) mainly includes countries from the South-East of the continent. This structure reflects the much higher capacity of Cluster 1 states to increase productivity in the medium and long term and also the competitive advantage over Cluster 2 countries, in particular.

Through annual clustering, we observe that among the states that belong to Cluster 1, only four managed to maintain their status each year, namely Denmark, France, Germany and the Netherlands, while at the opposite pole were Croatia and Romania, countries that permanently ranked in Cluster 2.

On the other hand, when we analyze the convergence trend through annual clustering, the results show that there are convergence processes in certain cases. For example, there are countries like Spain, Italy, Belgium or Czechia that have managed in certain periods to advance from Cluster 3 to Cluster 1, and even to stay there for a longer time (Portugal).

This reclassification can be explained by the favorable evolution of the index in 2022 compared to 2021, and by the decrease in the value of the final center of Cluster 1 to 0.75 in 2022, which indicates a decrease in the average performance level of the states in this group. Although the states that were already part of cluster 1 in 2021 maintained their position in 2022, they recorded decreases in performance, which reduced the overall level of the performing cluster and allowed the inclusion of Belgium, the Czech Republic, Italy and Spain in this category. On the other hand, the re-inclusion of Belgium, the Czech Republic and Italy in

Cluster 1 in 2024, after they were included in Cluster 3 in 2023, can be explained by the significant increase in the values of the analyzed index. Compared to the other states included in Cluster 1 in 2024, these countries recorded the most positive developments of the indicator, which brought them closer to the statistical profile specific to the group of high-performing states. As for Spain, its inclusion in Cluster 1 in 2025 can be explained by the significant increase in the index value compared to 2024, this being the largest positive evolution among all the countries analyzed. In this context, Spain's favorable dynamics contributed decisively to its repositioning among the high-performing countries.

In the analyzed context, the convergence processes observed in the case of Belgium, the Czech Republic and Italy, both in 2022 and 2024, can be explained inclusively by improving performance in terms of governance, infrastructure and data.

Another important remark is that many of the states that are mainly found in Cluster 1, in 2025 have registered a divergence process, moving into Cluster 3 (for example Austria, Luxembourg or Sweden) because in 2025 there were significant absolute decreases in the index compared to 2024.

Conclusions

Through the way the paper is structured and based on the results obtained, the objectives of the work has been achieved.

Most Western and Northern European countries register high performances in terms of AI Readiness, while at the opposite pole are mostly South-Eastern countries. This shows us, among other things, that the developed EU-27 countries are developing a potential competitive advantage in the medium and long term compared to the other member states.

It is important to note that there are countries like Portugal that are making progress in convergence with the most developed states, but also that Romania and Croatia have consistently recorded poor results.

The low level of AI readiness in countries such as Romania can have significant consequences on productivity and economic competitiveness, the efficiency of public administration, cybersecurity, or the labor market. In this context, it becomes imperative to develop and implement certain measures and policies to improve AI readiness, including: public and private investments in the development of digital infrastructure, granting tax facilities and subsidies for companies that invest in AI research and development, creating university programs focused on developing AI skills and professional training programs at the enterprise level for upskilling, and drafting strict regulations so that artificial intelligence is used ethically and transparently.

At the same time, improving the performance of low-performing states can be supported by various European Union policies, including by increasing financial allocations to states in lower clusters, with a distribution oriented according to the sub-dimensions in which deficits are recorded, as well as by strengthening and harmonizing the digital governance framework at European level.

The paper has also certain limitations, especially in terms of not focusing on the particular constituent dimensions that influence the total AI Readiness scores, and therefore the division into clusters. The analysis is focused on highlighting the distribution of AI readiness performances and convergence/divergence trends, without an in-depth examination of the associated explanatory factors.

This research can be expanded by addressing the aforementioned limitations and also by identifying specific potential solutions to increase the degree of convergence between states regarding AI readiness.

The paper is particularly aimed at the academic environment, representing a potential support for other research in the field of AI.

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Generative Artificial Intelligence (GenAI) usage statement:

No GenAI tool was used in the development of this paper.

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