THE NEW TRAJECTORIES OF ARTIFICIAL INTELLIGENCE A MULTIDIMENSIONAL ANALYSIS

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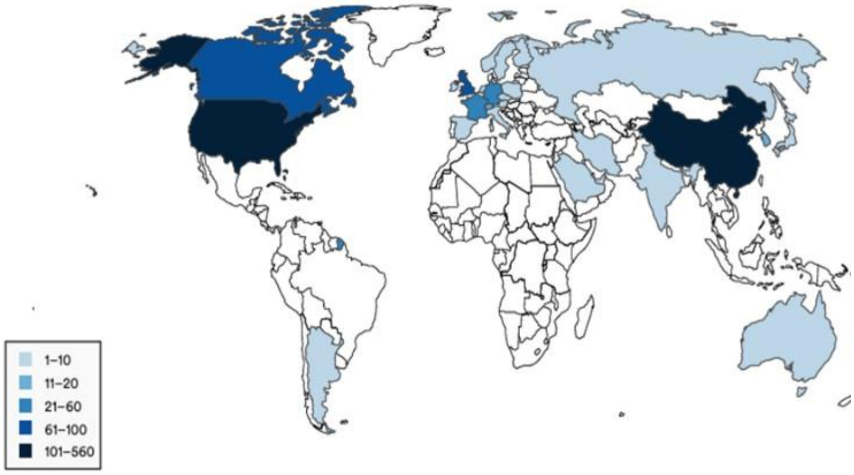
Abstract. Contemporary technological progress in the fields of statistics, artificial neural networks, and machine learning has generated remarkable advancements in Artificial Intelligence (AI) innovation. The proliferation of AI technologies is fundamentally transforming production methodologies, business paradigms, and organizational structures within both private sector enterprises and public administration institutions.
The present work examines principal indicators for the analysis and development of this novel advanced technology in the European context. Given the multidimensional characteristics of the study, following the analysis and description of individual dimensions, a multivariate analysis is conducted for territorial and temporal comparisons. This investigation offers significant contributions to understanding the contemporary and prospective AI landscape, with substantial ramifications for strategic decision-making across social, economic, technological, and industrial sectors.

1. Global and European Landscape in AI Development

The analysis of the global landscape reveals a significant concentration of relevant AI model development in advanced economies (Figs. 1 and 2) [1]. The United States, Canada, and several European countries exhibit the highest density of AI models, highlighting their role as technological leaders. China presents a moderate but significant concentration, while Europe shows a heterogeneous distribution with particular concentration in Nordic and Western countries[2].

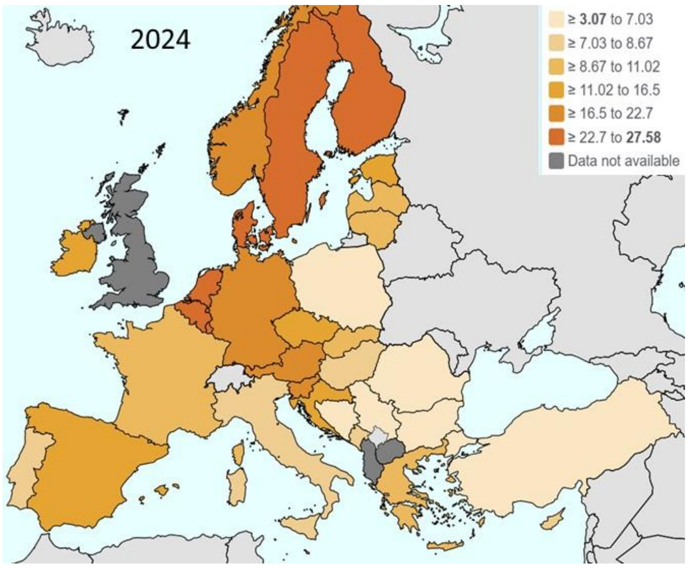
[1] EUROSTAT. 2025. *Use of artificial intelligence in enterprises*. Statistics Explained Statistics Explained (https://ec.europa.eu/eurostat/statisticsexplained).
[2] STANFORD UNIVERSITY HAI. 2025. *Artificial Intelligence*. Index Report 2025.

Figure 1 – *Number of notable AI models by geographical area, 2003-24 (Sum).*



Source: Epoch AI; Chart: 2025 Index AI report.

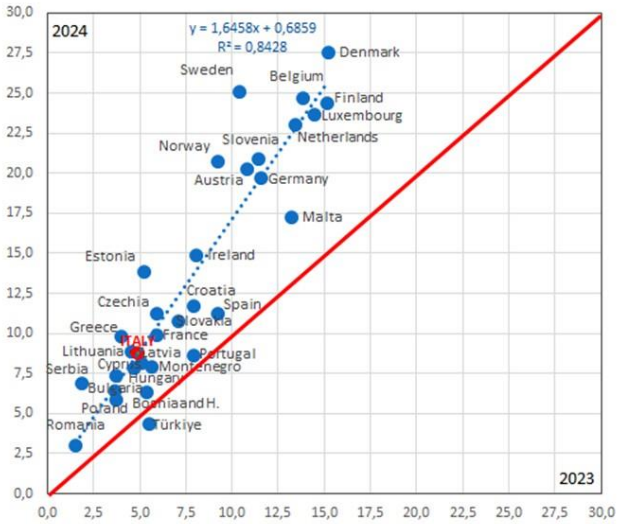
Figure 2 – *Enterprises using AI technologies, 2024 (%).*



Source: Eurostat data processing.

Analyzing temporal dynamics within the EU landscape, the 2023-2024 transition diagram reveals distinctive patterns of growth in AI adoption (Fig. 3). The positive correlation (R^2=0.8428) between adoption levels in the two consecutive years indicates structural stability among technological leaders. Nordic countries (Denmark, Sweden, Finland) and Benelux nations (Netherlands, Belgium, Luxembourg) maintain leadership positions with adoption rates exceeding 20%.

Figure 3 – *Transition diagram - Enterprises using AI technologies, 2023 and 2024 (% of enterprises).*

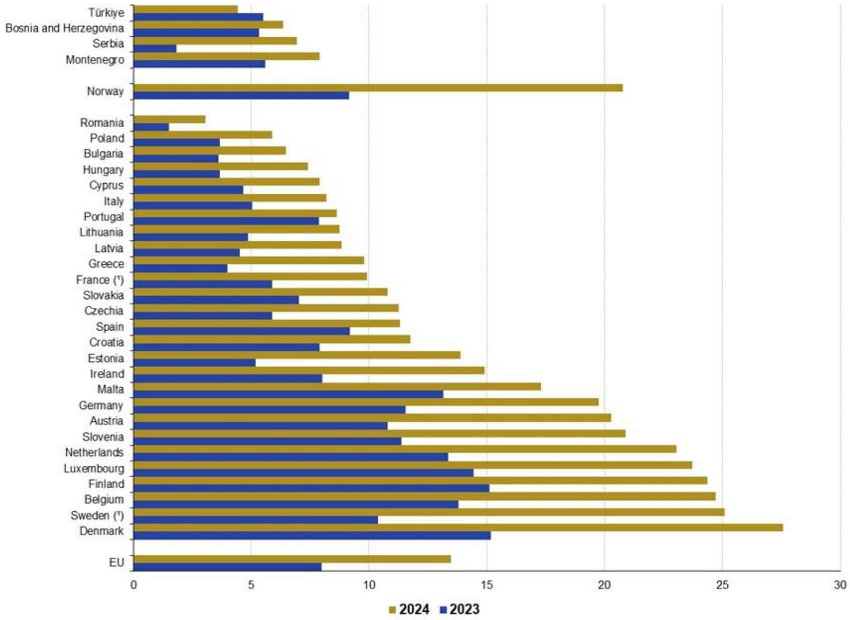


Source: Eurostat data processing.

Particularly significant is the positioning of countries: those above the regression line show accelerated growth in 2024, while those below the line exhibit more contained growth relative to the general trend. The EU average stands at approximately 13-14% in 2024, representing an increase from 2023. Figure 4 shows an overview of the evolution of AI investments in European enterprises between 2023 and 2024, confirming the important role of Nordic countries as AI technological leaders in Europe.

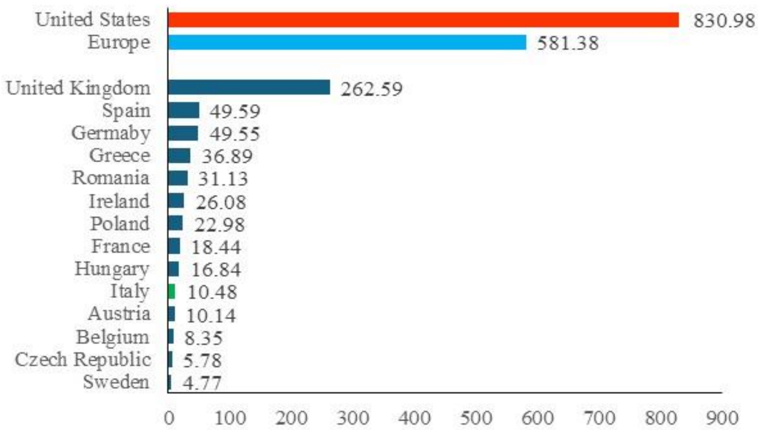
Public spending on AI contracts shows diversified trends (European Court of Auditors, 2024): the United States maintains consistent investment around 850 billion dollars (2023), while Europe presents significantly lower but growing values, with the United Kingdom (262.59 billion), Spain (43.59 billion), and Germany (49.55 billion) as the main investors (Fig. 5).

Figure 4 - *Enterprises using AI technologies, 2023 and 2024 (% of enterprises).*



Source: Eurostat data processing.

Figure 5 – *Public spending on AI-related contracts in select countries, 2023 (in billions US dollars)*



Source: Eurostat data processing.

2. Strategic Trajectories of EU Enterprises for AI Development through Exploratory PCA Analysis

2.1. Preliminary PCA analysis

The analysis was conducted on seven key indicators related to the adoption and development of artificial intelligence (AI) in European countries for 2023 (Tab. 1). Preliminary statistical validation confirmed the adequacy of the data for PCA analysis (Johnson, R. & Wichern, D.W. 2007). Examination of descriptive statistics immediately reveals the heterogeneity of the analyzed indicators in terms of means and variability (Tab. 2). Skewness indices highlight distributions deviating from normality: *AI Investments* (2.45) and *AI Patents* (2.24) with positive skewness. Conversely, the *Digital Skills* indicator (0.127) has an almost symmetric distribution. The leptokurtic distributions (kurtosis>3) for *AI Investments* (6.03), *AI Patents* (5.47), and *AI Startups* (3.91) indicate greater extreme concentrations with increased tails and outliers, while the platykurtic distributions (kurtosis<0) for *Digital Skills* (-1.28) and *AI Readiness Index* (-1.23) show opposite distributional patterns.

Table 1 – *AI indicators for European countries. 2023.*

Indicators		Source
B	AI Readiness Index	*AI Singapore (AISG)* [3]
C	AI Investiments	*European Court of Auditors and Commission EU*
D	Enterprises using AI	*Eurostat*
E	AI Startup	*Eurostat*
F	Digital Skill	*Eurostat*
G	AI Patents	*Epo Patent Index*
H	AI Publications	*Eurostat*

The combination of positive skewness and leptokurtosis in innovation indicators (*Investments*, *Patents*, and *Startups*) signals the presence of significant outliers representing European excellence hubs. Therefore, descriptive statistics make data normalization methodologically necessary to ensure analytically valid and interpretable results and justify the application of PCA as a dimensionality reduction technique (Abdi, H. & Williams, L. J. 2010).

[3] AI Singapore (AISG) constitutes a comprehensive national artificial intelligence program initiated by the National Research Foundation (NRF) with the objective of advancing Singapore's national capabilities in artificial intelligence research and development. AI Singapore. (2023). About AI Singapore. https://aisingapore.org/

Table 2 – *Descriptive statistics (a.v. and %).*

Descriptive statistics	AI Readiness Index	Investments in AI	Enterprises using AI	AI startups	Digital skills	AI patents	AI publications
Mean	65.5	962	7.76	125.0	71.7	308	1042
Median	63.2	520	6.70	95.0	70.1	195	780
Dev. Std	9.27	1156	4.30	104	9.53	279	785
CV%	14.15	120.16	55.41	83.2	13.3	90.58	75.33
Asymmetry[4]	0.234	2.45	0.548	1.97	0.127	2.24	1.74
Kurtosis[5]	-1.23	6.03	-0.817	3.91	-1.28	5.47	3.16

Pearson correlation analysis (Tab. 3 and Fig. 6) reveals significant and coherent relationships among most indicators, with coefficients ranging between 0.425 and 0.610 (all p<0.05).

Particularly strong is the correlation between the *AI Readiness Index* and *Enterprises using AI* (r=0.590, p=0.002), as well as between *AI Investments* and *AI Startups* (r=0.478, p<0.001).

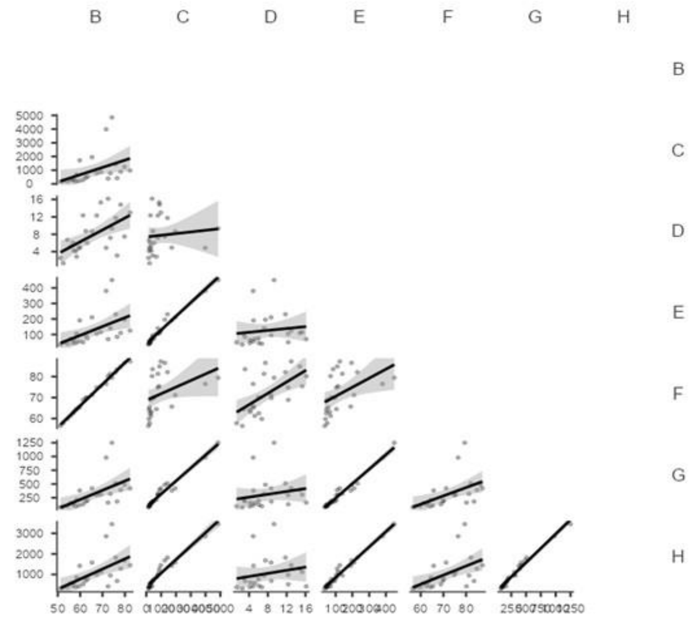
Table 3 – *Correlation matrix.*

Indicators	r	AI Readiness Index	Investments in AI	Enterprises using AI	AI startups	Digital skills	AI patents
Investments in AI	*r*	0.425 *	—				
	p	*0.034*	—				
Enterprises using AI	*r*	0.590 **	0.102	—			
	p	*0.002*	*0.626*	—			
AI startups	*r*	0.509 **	0.478 ***	0.125	—		
	p	*0.009*	*< .001*	*0.551*	—		
Digital skills	*r*	0.496 **	0.381	0.610 **	0.468 *	—	
	p	*0.003*	*0.060*	*0.001*	*0.018*	—	
AI patents	*r*	0.560 **	0.478 **	0.200	0.580 **	0.517 **	—
	p	*0.004*	*0.003*	*0.338*	*0.001*	*0.008*	—
AI Publications	*r*	0.581 **	0.567 **	0.207	0.482 **	0.537 **	0.589 **
	p	*0.002*	*0.002*	*0.320*	*0.002*	*0.006*	*0.002*

[4] Fisher's Asymmetry Index, $\gamma_1=(1/n)\ \Sigma[(x_i-\mu)/\sigma]^3$, measures how much the distribution deviates from symmetry. A value of 0 denotes perfect distributional symmetry; positive values (>0) indicate positive skewness with an extended right tail, negative values (<0) indicate negative skewness with an extended left tail.

[5] Pearson's Kurtosis coefficient, $Kurt = \Sigma(x_i-\mu)^4/n\sigma^4$, measures the degree of kurtosis as the arithmetic mean of the fourth moments of the standardized variable $Z=(x-\mu)/\sigma$.

Figure 6 – *Correlation graph.*



Furthermore, the analysis demonstrated the suitability of the data for PCA application through several statistical tests (Tabs. 4 and 5). Bartlett's Sphericity Test showed highly significant results (χ^2=382, df=21, p<0.001), confirming that variables are sufficiently correlated to justify factor analysis (Bartlett, M.S. 1950). The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy reached an overall value of 0.771, considered "good" according to standard criteria, with individual values for each indicator ranging between 0.633 and 0.915, all above the acceptability threshold of 0.5 (Kaiser, M.W. & Olkin, I. 1978). Therefore, following preliminary statistical analyses, values were preventively normalized to ensure analytically valid and interpretable results using PCA.

Table 4 – *Bartlett's Sphericity Test.*

χ^2	gdl	p
382	21	< .001

Table 5 – *KMO Sampling Suitability Measure*.

Indicators	MSA
Global	0.771
AI Readiness Index	0.633
Investments in AI	0.773
Enterprises using AI	0.656
AI Startups	0.915
Digital skills	0.675
AI patents	0.893
AI publications	0.898

2.2. PCA results

Analysis of initial eigenvalues revealed a two-component structure that collectively explains 93.0% of total variance (Tab. 6 and Fig. 7). The first component explains 68.6% of variance (eigenvalue=4.803) while the second component contributes an additional 24.4% (eigenvalue=1.707). The scree plot clearly confirms this bi-factorial structure, showing a distinct *elbow* after the second component, with all subsequent eigenvalues below 1.0. This distribution indicates a strong concentration of variability in the first two factors, suggesting the existence of two fundamental latent dimensions in the European AI landscape.

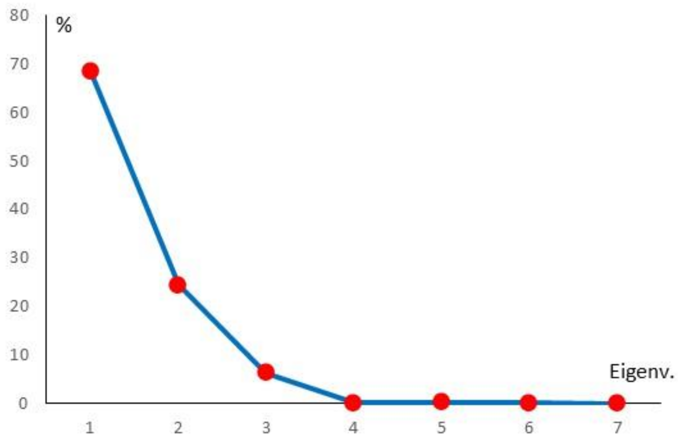
First Component: *Research and Innovation Ecosystem*. The first component is characterized by high loadings for indicators related to investments and research output: *AI Investments* (0.985), *AI Startups* (0.978), *AI Patents* (0.963), and *AI Publications* (0.958). This represents the "*Research and Innovation Ecosystem*" dimension in artificial intelligence, characterizing countries by their capacity to develop and sustain technological innovation, scientific research, and entrepreneurship in AI.

Second Component: *Diffusion and Digital Capacity*. The second component is dominated by the *AI Readiness Index* (0.888), *Digital Skills* (0.907), and *Enterprises using AI* (0.845). This represents the "*Diffusion and Digital Capacity*" dimension, reflecting the degree of AI penetration in the economic and social fabric of European countries.

Table 6 – *Initial Eigenvalues.*

Components	Eigenvalues	% of Variance	Cumulative %
1	480.323	686.175	68.6
2	170.663	243.805	93.0
3	0.44733	63.905	99.4
4	0.01826	0.2609	99.6
5	0.01688	0.2411	99.9
6	0.00608	0.0869	100.0
7	0.00158	0.0226	100.0

Figure 7 – *Cumulative Plot.*



2.3. Cluster results

PCA biplot visualization and K-means clustering highlighted positioning and segmentation in the European landscape, identifying two distinct clusters reflecting differentiated strategies in the European context (Figs. 8 and 9):

Cluster 1: *Technological and Innovation Leaders*

Includes countries from central-northern Europe such as France, Germany, Netherlands, Denmark, Finland, Sweden, and Belgium. These countries position themselves positively on both dimensions, showing both a strong research and innovation ecosystem and high AI adoption.

Cluster 2: *Countries in Transition*

Primarily comprises countries from central-eastern and southern Europe (Italy, Spain, Poland, Romania, Bulgaria, etc.) that show lower performance, particularly in the first component related to innovation. The validity indices of the two clusters, Silhouette and DB, show good separation between the two clusters (Tab. 7)[6].

Figure 8 – *K-means Plot.*

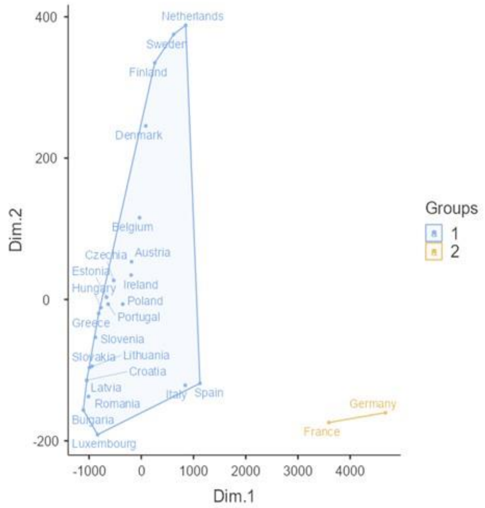


Figure 9 – *PCA – Biplot.*

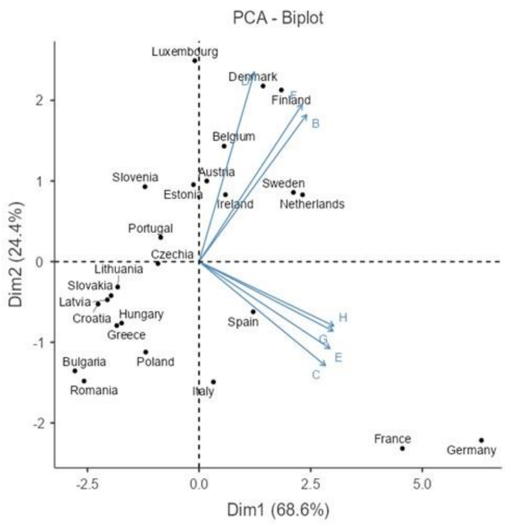


Table 7 - *Validation Indices.*

Index	Value
Silhouette	0,687
DB (Davies-Bouldin)	0,356

The strong correlation between dimensions, as indicated by the convergent arrows in the biplot, suggests that AI development requires a systemic approach that integrates technological capabilities and application diffusion.

This analysis provides an empirical framework for understanding different AI development trajectories in Europe and identifies key dimensions on which policymakers should focus efforts to promote digital competitiveness.

[6] The *Silhouette* and *DB (Davies-Bouldin) Validation indices* are used to objectively evaluate the quality of data partitioning into clusters. The *Silhouette index* calculates the average distance between a point and all other points within its own cluster, and the average distance between the point and all points located in different clusters. A *Silhouette* value close to 1 indicates good cluster separability, while a value close to -1 indicates poor separability. The *DB index* calculates the average distance between cluster centers and measures how compact and separated the clusters are. A value below 1 indicates good separation.

3. Conclusions

The principal component analysis conducted on seven key artificial intelligence indicators in European countries revealed a bidimensional structure that characterizes the European AI landscape. The results highlight the existence of two fundamental strategic trajectories that distinguish European countries in their approach to AI development.

The first dimension, *AI Innovation and Research Ecosystem*, reveals how certain countries have developed an integrated system that fuels research and development in the AI sector.

The second dimension, *Diffusion and Digital Capacity*, emphasizes the importance of the capacity for adoption and implementation of AI technologies at a systemic level.

Cluster analysis identified two distinct groups of countries: the *Innovation Leaders* (primarily Nordic and central-northern European countries) that excel in both dimensions, and the "Countries in Transition" (predominantly central-eastern and southern Europe) that present significant margins for improvement, particularly in the innovation ecosystem, Italy is part of this cluster. The presence of these two distinct clusters indicates a significant gap between leading countries and those lagging behind, suggesting that AI development requires a dualistic approach through differentiated policies to promote technological convergence at the European level.

On one hand, it is necessary to build solid foundations of research and innovation through targeted investments supporting technological entrepreneurship. On the other hand, it is fundamental to develop adoption capabilities and digital skills to ensure effective diffusion of AI technologies in the real economy.

The strong correlation between the two dimensions (cumulative variance of 93%) indicates that the most competitive countries in AI are those that successfully integrate innovative capabilities and application diffusion. This suggests that public policies should adopt a systemic vision, avoiding fragmented approaches that privilege only one of the two aspects.

In conclusion, PCA analysis provides a strategic map of the European AI landscape, highlighting how success in this sector depends on the ability to simultaneously orchestrate technological innovation and digital transformation of the socio-economic fabric (Lecardane, G. 2024). Countries aspiring to leadership positions will necessarily need to invest in both dimensions, developing robust innovation ecosystems while concurrently promoting widespread diffusion of AI skills and applications.

Countries in transition require comprehensive strategies that build both research infrastructure and digital transformation capabilities, rather than isolated interventions in specific areas (European Commission, 2025).

The bidimensional structure identified through PCA analysis provides important insights for European AI policy development.

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