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A COMPARATIVE STUDY OF THE RELATIONSHIPS BETWEEN AI USE, EMPLOYMENT, ECONOMIC PERFORMANCE, AND SUSTAINABILITY IN THE EU COUNTRIES

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Abstract. The swift adoption of artificial intelligence (AI) across EU economies has sparked heightened debate among scholars and policymakers about its association with labor market dynamics, economic outcomes, and sustainability objectives. This research investigates the cross-sectional links between enterprise-level AI adoption and key socio-economic indicators across EU countries, including total employment, the proportion of highly educated science and technology workers, GDP per capita, and the Sustainable Development Goals Index (SDGI). Using a comparative and multi-method approach, the study combines exploratory factor analysis, general linear model estimations, and cluster analysis to identify structural patterns and group countries with similar digital and developmental traits. Results show consistent links between AI adoption and higher economic performance, as well as a larger share of science and technology professionals. The relationships with overall employment and sustainability indicators are weaker but still present. The cluster analysis reveals diverse yet cohesive national profiles, reflecting differences in digital readiness, human capital, and institutional factors across the EU. The study's primary contribution is to combine employment structures, economic performance, and sustainability into a comprehensive cross-sectional framework, providing a detailed comparison of AI-related patterns across the EU. Its findings provide policymakers with a solid empirical foundation for assessing how the diffusion of AI supports inclusive growth and sustainability goals.

Keywords: artificial intelligence, employment, education level, economic performance, sustainability, EU countries.

JEL Classification: J21, Q56.

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1. Introduction

The adoption of artificial intelligence (AI) across EU economies has garnered increasing scholarly attention due to its effects on business outcomes, labor markets, and overall growth. In business and economics, AI is widely regarded as a technology associated with higher productivity and innovation, transforming how companies operate and compete (Acemoglu & Restrepo, 2018; Brynjolfsson et al., 2021). Within the EU, this transition is particularly notable, given the coexistence of highly developed digital economies and member states still in the early stages of technological adoption.

Existing empirical evidence consistently shows that AI adoption is associated with improved economic performance and a higher concentration of science and technology professionals, reflecting shifts in skill demands and organizational capabilities (Damioli et al., 2021; Liang et al., 2025). However, research on overall employment levels and sustainability outcomes yields mixed results, suggesting that digitalization is not consistently associated with broader social progress (Bessen et al., 2020; Almusharraf, 2025; Dauvergne, 2021). These findings imply that the economic and societal effects of AI spread and develop concurrently but not necessarily at the same pace.

Despite increasing EU-focused research, much of it examines employment, economic performance, and sustainability outcomes separately, often using narrow indicators. Consequently, researchers have paid less attention to integrative analytical approaches that explore how these aspects coexist within a single comparative framework. This is particularly relevant in the EU, where policies aim to align digital transformation with inclusive growth and sustainability (European Commission, 2020).

To fill this gap, this study investigates the cross-sectional relationships between enterprise-level AI adoption and key socio-economic indicators across EU countries, including total employment, the proportion of workers in science and technology, GDP per capita, and SDG Index scores. By applying exploratory factor analysis and cluster analysis, the research identifies patterns and groups of countries with similar digital, economic, and sustainability profiles. Its contribution lies in providing an integrated perspective that enhances current EU-level research by simultaneously examining multiple dimensions of AI-driven development within a unified framework, relevant for both economic analysis and policy discussions.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature and develops the research hypotheses. Section 3 presents the research methodology, including the data and methods used. Section 4 reports the empirical results. Section 5 discusses the findings and outlines policy implications, limitations, and directions for future research. Finally, Section 6 concludes the paper.

2. Literature review

Recent technological changes, driven by digitalization and the growth of artificial intelligence (AI), are reshaping economies and societies across the European Union in fundamental ways. As AI becomes more integrated into productive systems, its effects on labor markets, economic performance, and sustainability have become a key focus of research. Scholars present a complex and often contradictory picture, in which AI displaces jobs in some sectors while creating new job opportunities and boosting overall productivity (Acemoglu & Restrepo, 2018, 2020; Khogali & Mekid, 2023).

Academic literature highlights a key tension in understanding AI's dual role. It raises significant concerns about automation and job loss, especially in sectors reliant on repetitive tasks (Frey & Osborne, 2017; Bowles, 2017; Ajiga et al., 2024), a problem that is particularly acute in the older EU member states with highly technologized economies (Chiacchio et al., 2018). At the same time, AI holds considerable promise for job creation in new fields such as information technology, data analysis, and digital services (Dauth et al., 2017).

This dual nature becomes clearer when examining its regional effects. In newer EU member states such as Romania and Poland, AI has helped boost employment through infrastructure upgrades and economic convergence (Guliyev, 2023). However, the literature also indicates that without targeted policies and investments in human capital, AI tends to polarize labor markets and widen existing inequalities (Bessen, 2020; Bessen et al., 2020; Acemoglu & Restrepo, 2019).

Another key research area examines AI's effects on economic growth and sustainability. Theories of endogenous growth, developed by Aghion and Howitt (1992) and later expanded by Aghion et al. (2018) and Aghion et al. (2019), are supported by empirical evidence from Kalai et al. (2024), who analyze AI's influence on GDP across 30 European countries and find significant, though uneven, positive effects on growth. Scholars acknowledge AI's role in increasing total factor productivity, enhancing energy efficiency, and enabling more optimized decision-making processes (Brynjolfsson & McAfee, 2014; Brynjolfsson et al., 2017).

Ballestar et al. (2021) and Gaglio et al. (2022) highlight that digital integration boosts productivity only when innovation and skills mediate the relationship. In this view, AI catalyzes transformation, but only in settings with strong digital infrastructure that supports its adoption (Myovella et al., 2020; Azu & Nwauko, 2021).

Research on sustainable development within the EU emphasizes the connections between technological progress, energy efficiency, human capital, and innovation (Cockburn et al., 2018; Jēdrzejczak-Gas et al., 2021).

2.1. AI and employment in science and technology fields

Research indicates that AI's impact on employment depends largely on a country's occupational structure and workforce skills. Many studies show that automation technologies do not affect all job types equally; instead, they cause occupational polarization, disproportionately affecting low-skilled workers. Recent research by Liang et al. (2025) shows that the spread of AI decreases demand for low-skilled labor while increasing demand for medium- and high-skilled workers, especially in areas with advanced technological infrastructure and high levels of digitalization (Plikas et al., 2024). These effects are particularly significant for women, who often hold roles more vulnerable to technological displacement.

This dynamic is well captured by the task-based approach developed by Autor et al. (2003) and further refined by Autor (2015), Autor and Salomons (2018), and Acemoglu and Restrepo (2020). Their model shows that automation targets specific tasks rather than entire jobs. AI does not entirely replace human labor but reorganizes it, redistributing tasks between humans and machines. Mid-level jobs that rely on routine or repetitive tasks face the highest risk of decline, while cognitively demanding, decision-based, or creative professions, particularly in science and technology, tend to grow stronger (Atkinson, 2018).

Further labor market analyses of the EU's digital transformation confirm this pattern. In advanced economies, AI adoption often substitutes human labor, especially when adaptive public policies are lacking. This substitution is associated with rising structural unemployment and deepens socio-economic inequalities (Acemoglu & Restrepo, 2019).

Based on this theoretical and empirical foundation, we propose the following hypothesis:

Hypothesis H1. Across EU countries, higher levels of enterprise AI adoption tend to co-occur with a higher share of workers employed in science and technology sectors. In contrast, associations with overall employment levels appear weaker.

2.2. AI, GDP, and sustainability scores

Kalai et al. (2024) show that advanced econometric models indicate AI has a positive association with GDP per capita (GDPpc) across European countries. However, these effects vary widely by the type of technological shock. Further empirical research supports these conclusions. For example, Damioli et al. (2021) demonstrate the innovative and multiplicative benefits of AI by showing a strong link between labor productivity in small and medium-sized businesses and AI-related patents, especially in the service sector. Erdil and Besiroglu (2023), Graetz and Michaels (2018), Baldwin (2019), and others connect the use of industrial robots, which stand in for artificial intelligence, to significant economic growth and rising wages.

The importance of AI, however, extends beyond economic factors. Recent studies examine the link between artificial intelligence (AI) and sustainability, arguing that AI can actively support the achievement of the SDGs (Jēdrzejczak-Gas et al., 2021). AI enables better resource management, reduces energy use, and facilitates the integration of renewable energy into industrial processes. Specifically, energy efficiency has become a key way in which AI helps cut carbon emissions and meet climate targets outlined in the SDGs (Yang et al., 2021).

However, academics also warn of systemic risks. For example, the so-called "rebound effect" suggests that efficiency gains from innovative technologies may unintentionally raise overall energy consumption, reducing or negating climate benefits (Liu, 2023; Dauvergne, 2021). Without a simultaneous shift to renewable energy sources, widespread AI adoption could worsen the negative externalities of economic activity (Ahmed & Elfaki, 2024). This underscores the importance of regulatory frameworks that link AI deployment to sustainable energy policies and resource-use reduction strategies.

However, these benefits are not shared equally. The Gini index rose by 12% during the study period, signaling rising income inequality, partly driven by the displacement of low-skilled workers and the disproportionate pay for high-skilled talent (Frey & Osborne, 2017). Hémous and Olsen (2022) and Badet (2021) emphasize that, without targeted policies and effective reskilling initiatives, AI could deepen social gaps, benefiting high-tech sectors while marginalizing less developed regions.

Based on this body of literature, we suggest the following hypothesis:

Hypothesis H2. Across EU countries, higher levels of AI adoption are associated with higher GDP per capita and more favorable Sustainable Development Goals Index (SDGI) scores.

2.3. Heterogeneity within the EU: regional clusters of digital performance

Scholarly research consistently highlights significant disparities among European Union member states in digital infrastructure, labor market structures, economic performance, and sustainable development (Jēdrzejczak-Gas et al., 2021; Bluszcz, 2016; Mura & Donath, 2023). These differences stem from a mix of historical, institutional, and structural factors that shape each country's capacity to adopt new technologies, especially artificial intelligence (AI), effectively and fairly.

In this context, taxonomic and multicriteria studies provide important insights into how EU member states cluster based on shared characteristics, offering a more unified view of the Union's internal structure. Analyses by Sompolska-Rzechuła (2020) and Kiselakova et al. (2020) categorize European countries using economic, environmental, and social indicators, revealing relatively homogeneous clusters with similar levels of development, digitalization, and sustainability.

A particularly revealing example is the contrast between Nordic countries, such as Sweden, Finland, and Denmark. and those in Southeastern Europe. The Nordic states, along with Austria, consistently rank highly in digital infrastructure, innovation capacity, human capital, and progress toward the SDGs (Bak & Cheba, 2018; Jēdrzejczak-Gas et al., 2021). Their achievements trace back to the implementation of the Europe 2020 Agenda and have been further strengthened by a strategic focus on inclusive digitalization and sustainability (European Union, 2019).

In contrast, countries in Southeastern Europe, including Romania, Bulgaria, and Greece, still face structural challenges, such as low levels of SME digitalization, significant gaps in digital skills, and underdeveloped technological infrastructure (Brodny & Tutak, 2022). Specifically, disparities among small, medium, and large enterprises in Central and Eastern Europe are closely linked to economic indicators such as GDP per capita and labor productivity, which help explain the region's uneven economic performance relative to Western European countries (Brodny & Tutak, 2022). These issues directly impede the effective adoption and use of AI, increasing the risk of new layers of technological fragmentation within the European Union.

Building on this perspective, we suggest the following hypothesis based on the existing literature:

Hypothesis H3. EU member states tend to form relatively homogeneous groups, influenced by similarities in AI adoption, employment patterns, the percentage of science and technology workers in GDP per capita, and SDGI scores.

3. Research methodology

3.1. Research design

This study employs a cross-sectional design to examine the relationship between enterprise-level AI adoption and labor market, economic, and sustainability indicators across EU member states. Focusing on EU countries ensures analytical consistency and data accessibility. However, it also results in a relatively small sample size, limiting statistical power and reducing the ability to generalize findings outside the EU.

The cross-sectional design is determined by the availability of AI-related data over time. Current Eurostat data on firm-level AI adoption, which may have macroeconomic and societal implications, is available only for 2023 and 2024. This limited time frame restricts the ability to perform longitudinal or panel analyses that could explore dynamic associations, lag structures, or long-term adjustments. Consequently, the study emphasizes current associations instead of establishing causal relationships.

Given these limitations, the research relies on exploratory methods, including factor analysis, cluster analysis, and general linear model (GLM) estimations, for descriptive and exploratory purposes. These approaches help identify structural patterns, cross-country similarities, and associations, but are not intended to establish causality. Methodological concerns such as endogeneity, reverse causality, and omitted-variable bias, which may be linked to education systems, institutional quality, capital intensity, or innovation capacity, are recognized as inherent limitations of the chosen approach.

3.2. Selected variables

The variables are chosen based on their theoretical importance, ability to be compared across EU countries, and data availability for the reference period. The study includes indicators related to AI adoption, labor-market employment, advanced human skills, economic performance, and sustainability outcomes (see Table 1).

Table 1. Research variables

Variable	Dataset	Measures	References
AI	Enterprises use at least one of the AI technologies	Percentage of enterprises	Eurostat (2025a)
EMPL	Total employment	Percentage of the total population	Eurostat (2025b)
HRST	Persons with tertiary education (ISCED) and employed in science and technology	Percentage of population in the labour force	Eurostat (2025c)
GDPpc	GDP per capita in PPS	Volume indices of real expenditure per capita (in PPS_EU27_2020 = 100)	Eurostat (2025d)
SDGi	SDGi score	Weighted score	Sustainable Development Solutions Network [SDSN] (2025)

AI diffusion is measured by the percentage of enterprises using at least one AI technology, reflecting the level of digital integration within the private sector. Labor market trends are reflected in total employment numbers and the share of workers with tertiary education in STEM fields, which capture overall labor participation and the composition of the high-skilled workforce. Economic performance is evaluated using GDP per capita based on purchasing power parity, enabling meaningful comparisons across countries. Sustainability is gauged using the Sustainable Development Goals Index (SDGi), a comprehensive metric that encapsulates progress across social, economic, and environmental domains.

3.3. Methods

The empirical analysis starts with an exploratory factor analysis (EFA), used as a descriptive tool to examine whether the chosen, theoretically important, and directly observable indicators show consistent patterns across countries. Instead of seeking deeply latent constructs, this study uses EFA to examine whether related variables share sufficient variance to be summarized by fewer dimensions.

Two distinct EFA models are developed, each reflecting a different aspect of the study's focus. The first model analyzes the combined behavior of AI adoption, total employment, and the proportion of tertiary-educated workers in science and technology, enabling an investigation of how digital adoption relates to labor-market engagement and high-level human capital. The second model examines AI adoption alongside GDP per capita and sustainability performance, as indicated by the Sustainable Development Goals Index, highlighting how digital diffusion correlates with economic capacity and overall development goals.

Formally, the relationship between observed variables and extracted factors is expressed as Eq. (1):

$$X = \mathrm{LF} + \in, \tag{1}$$

X – observed variables; L – matrix of factor loadings; F – latent factors; $\in$ – errors.

Substantively, the two-factor models aim to determine whether the combined patterns of AI adoption, labor market indicators, economic performance, and sustainability metrics can be seen as part of a broader descriptive pattern related to sustainable development, especially amid digitalization and employment pressures. This view recognizes that digital transformation, labor market changes, and sustainability issues tend to develop together within particular national development profiles. Consequently, the factors serve as concise summaries of these relationships, providing a descriptive basis for subsequent analysis.

To further examine cross-sectional associations between AI adoption and selected outcome variables, the study employs multiple linear regression within the general linear model (GLM) framework, specified as Eq. (2):

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n + \in, \quad (2)$$

Y – dependent variable; $X_1, X_2, \ldots, X_n$ – independent variables; β_0 – intercept; $\beta_1, \beta_2, \ldots, \beta_n$ – regression coefficients; $\in$ – error.

These estimates are explicitly understood as cross-sectional and associative, reflecting relationships observed at a single point in time rather than indicating causality. Consequently, issues such as endogeneity, reverse causality, and omitted-variable bias are acknowledged as inherent limitations of the empirical approach.

Cluster analysis played a key role in classifying countries by structural similarities, enabling the identification of homogeneous groups based on AI adoption, economic performance, and progress toward SDGs. The average distance between clusters is calculated as Eq. (3):

$$d_{ij} = \frac{1}{kl} \sum_{i=1}^{k} \sum_{j=1}^{l} d\left(X_i, Y_j\right), \quad (3)$$

$X_{1,} X_{2,}, \ldots, X_k$ – observations from cluster 1; $Y_{1,} Y_{2,}, \ldots, Y_l$ – observations from cluster 2; $d(X, Y)$ – distance between a subject with observation vector x and a subject with an observation vector; k, l – cases.

4. Results

4.1. AI adoption and labor market structure

To test Hypothesis H1, the analysis employs both exploratory factor analysis (EFA) and general linear model (GLM) estimations together, aiming to identify patterns of association across the data regarding artificial intelligence adoption and important labor market features. EFA is used here in an exploratory, descriptive capacity to determine whether a small group of related, observable variables shows sufficient shared variation to capture a broader pattern of co-variation across variables, rather than uncovering complex latent factors.

The initial correlation matrix shows positive and statistically significant links between AI adoption and both labor market indicators examined (see Table 2). The correlation between AI and the proportion of tertiary-educated individuals working in science and technology (HRST) is moderate (0.495) and highly significant ($p < 0.001$), indicating a consistent relationship between digital adoption and the concentration of highly skilled human capital. Conversely, the correlation between AI adoption and total employment (EMPL) is weaker (0.270) but still statistically significant ($p = 0.024$), suggesting a more limited and variable connection at the aggregate employment level.

Table 2. Correlation matrix, KMO and Bartlett's test for the model of relationships between AI, EMPL, and HRST

			AI	EMPL	HRST
Correlation	AI		1.000	0.270	0.495
	EMPL		0.270	1.000	0.235
	HRST		0.495	0.235	1.000
Sig. (1-tailed)	AI			0.024	0.000
	EMPL		0.024		0.044
	HRST		0.000	0.044	
Kaiser-Meyer-Olkin Measure of Sampling Adequacy					0.589
Bartlett's Test of Sphericity		Approx. Chi-Square			19.018
		df			3
		Sig.			0.000

The factor analysis suitability tests suggest that the findings should be approached within an exploratory context. The Kaiser–Meyer–Olkin (KMO) measure is 0.589, indicating moderate sampling adequacy and suggesting that the shared variance among variables is sufficient, though not optimal, for factor extraction. Moreover, Bartlett's test of sphericity is highly significant ($p < 0.001$), confirming meaningful correlations among the variables. These diagnostics support the cautious use of a single component to summarize the observed co-variation, while also signaling that the results should not be taken as evidence of a strongly defined latent factor.

The exploratory analysis assesses whether the three variables, AI adoption, HRST, and EMPL, share a shared variation pattern. As shown in Table 3, this component accounts for a large share of the variance in AI (67.5%) and HRST (64.5%), but a smaller share in total employment (36.2%). All three variables load positively on the same component, with higher loadings for AI and HRST and a lower, yet still meaningful, loading for EMPL.

Instead of viewing this component as a latent causal factor, it is treated as a composite descriptive reduction that can be interpreted as summarizing patterns related to labor-market adaptation to digitalization.

Table 3. Communalities and factor matrix for the model of relationships between AI, EMPL, and HRST

	Initial	Extraction	Factor 1
AI	1.000	0.675	0.821
EMPL	1.000	0.362	0.602
HRST	1.000	0.645	0.803

Here, AI adoption is more closely linked to the growth of high-skilled employment rather than overall employment changes. This component explains 56.07% of the total variance, as shown in Table 4, supporting its use as a descriptive summary of common cross-country differences within this limited-variable framework.

To supplement these exploratory findings, GLM analyses examine the current relationships between AI adoption and two labor-market indicators. As shown in Table 5, AI adoption is significantly and positively associated with HRST ($B = 0.465$, $p < 0.001$), accounting for 24.5% of the variation in the share of science and technology workers. The statistical power for this relationship is high (0.981), indicating a strong cross-sectional association.

Table 4. Total variance explained for the model of relationships between AI, EMPL, and HRST

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	1.682	56.068	56.068	1.682	56.068	56.068
2	0.815	27.161				
3	0.503	16.771				

In contrast, the link between AI adoption and total employment is weaker. While the coefficient is positive and statistically significant (B = 0.188, p = 0.048), the model explains only 7.3% of the variance in EMPL, and the observed power is modest (0.510). This implies that overall employment outcomes are associated with a broader range of contextual factors not captured in the current analysis specification.

Table 5. Parameter estimates for the model of relationships between AI, EMPL, and HRST

Dependent Variable	Parameter	B	Std. Error	t	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power[a]
EMPL	Intercept	74.983	1.207	62.123	0.000	0.987	62.123	1.000
	AI	0.188	0.093	2.022	0.048	0.073	2.022	0.510
HRST	Intercept	21.036	1.472	14.293	0.000	0.797	14.293	1.000
	AI	0.465	0.113	4.110	0.000	0.245	4.110	0.981

Overall, the EFA and GLM findings offer consistent descriptive support for Hypothesis H1, showing that AI adoption more reliably relates to qualitative shifts in the labor market, particularly the concentration of high-skilled human capital, rather than widespread changes in total employment rates.

4.2. AI adoption, economic performance, and sustainability

Hypothesis H2 is tested within the same exploratory-complementary approach, which uses EFA and GLM to examine cross-sectional links among AI adoption, economic performance, and sustainability outcomes. The correlation matrix shows positive, statistically significant relationships between AI adoption and both GDPpc and the Sustainable SDGi, as shown in Table 6.

The correlation between AI and GDPpc is 0.478 ($p < 0.001$), while the association between AI and SDGi is stronger at 0.530 ($p < 0.001$). Notably, the correlation between GDPpc and SDGi is relatively low (0.142) and statistically insignificant, suggesting that economic performance and sustainability outcomes capture different aspects of national development, even though both relate to AI adoption.

nded for confirmatory factor analysis. However, due to the small number of variables and the cross-sectional dataset, this value is considered borderline but acceptable for exploratory analysis. Importantly, Bartlett's test of sphericity is highly significant ($p < 0.001$), indicating that the correlation matrix differs from an identity matrix and that the variables share enough common variance to justify factor extraction. Thus, the resulting component is regarded as an exploratory indicator rather than a definitive latent factor, mainly to support comparative analysis and encourage further research as longer time series and more comprehensive AI diffusion datasets become available.

Table 6. Correlation matrix, KMO and Bartlett's test for the model of relationships between AI, GDPpc, and SDGi

			AI	GDPpc	SDGi
Correlation	AI		1.000	0.478	0.530
	GDPpc		0.478	1.000	0.142
	SDGi		0.530	0.142	1.000
Sig. (1-tailed)	AI			0.000	0.000
	GDPpc		0.000		0.153
	SDGi		0.000	0.153	
Kaiser-Meyer-Olkin Measure of Sampling Adequacy					0.498
Bartlett's Test of Sphericity		Approx. Chi-Square			31.272
		df			3
		Sig.			0.000

The Kaiser–Meyer–Olkin (KMO) statistic is 0.498, just below the usual thresholds recom-meThe exploratory factor analysis assesses whether these three variables display a shared pattern of co-variation. As reported in Table 7, the extracted component explains a substantial share of variance for AI (80.6%), a moderate share for SDGi (52.6%), and a lower yet meaningful share for GDPpc (45.6%). All variables load positively on a single component, indicating consistent co-variation across EU member states.

Table 7. Communalities and factor matrix for the model of relationships between AI, GDPpc, and SDGi

	Initial	Extraction	Factor 1
AI	1.000	0.806	0.898
GDPpc	1.000	0.456	0.676
SDGi	1.000	0.526	0.725

This component summarizes a set of co-varying indicators related to sustainable development, reflecting how AI adoption aligns with economic capacity and sustainability outcomes. It accounts for 59.59% of the total variance, as detailed in Table 8, highlighting its usefulness as a descriptive summary of cross-country differences in this analysis domain.

Table 8. Total variance explained for the model of relationships between AI, GDPpc, and SDGi

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	1.788	59.593	59.593	1.788	59.593	59.593
2	0.859	28.623				
3	0.354	11.784				

The GLM estimates in Table 9 provide further insight into these relationships at the variable level. AI adoption shows a significant positive association with GDP per capita (B = 2.880, $p < 0.001$), accounting for 22.9% of the variance. Similarly, the relationship with SDGi is positive and statistically significant (B = 0.372, $p < 0.001$), explaining 28.0% of the variance. Both models show high observed power, indicating reliable cross-sectional results relationships.

Consistent with the study's cross-sectional design, these results are interpreted as associative rather than causal. They indicate that higher levels of AI adoption tend to co-occur with stronger economic performance and more favorable sustainability outcomes, while recognizing that these relationships are likely shaped by broader institutional, educational, and structural factors not explicitly modeled here.

Table 9. Parameter Estimates for the model of relationships between AI, GDPpc, and SDGi

Dependent Variable	Parameter	B	Std. Error	t	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power
EMPL	Intercept	70.983	9.539	7.441	0.000	0.516	7.441	1.000
	AI	2.880	0.734	3.926	0.000	0.229	3.926	0.971
HRST	Intercept	67.320	1.076	62.582	0.000	0.987	62.582	1.000
	AI	0.372	0.083	4.502	0.000	00.280	4.502	0.993

In line with the study's cross-sectional scope, the results for Hypothesis 2 are interpreted strictly as descriptive associations. The findings indicate that AI adoption tends to be associated with higher levels of economic performance and sustainability indicators, without implying any directional or causal linkage. These observed patterns are likely shaped by a complex set of institutional, educational, and structural characteristics that are not explicitly captured within the current empirical framework.

A cluster analysis of EU member states, based on key variables such as AI adoption rates in enterprises, total employment, the share of science and technology specialists in the active population, GDPpc, and the SDGi score, offers a precise and nuanced portrait of how countries align or diverge in their digital and socio-economic paths. Figure 1 and Table A1 (in the Appendix) show the two main clusters, A and B, each with two subclusters.

The cluster analysis offers a structured approach to contextualize the cross-sectional associations found via exploratory factor analysis and GLM estimates. Instead of functioning solely as a descriptive regional taxonomy, the clustering results demonstrate how different combinations of AI adoption, labor market structure, economic performance, and sustainability outcomes create coherent national development profiles across EU member states.

The two primary clusters reveal differences in how digital transformation relates to human capital and institutional capacity. Cluster A includes countries whose indicators are nearer to the EU average and where AI adoption is still developing. Within this group, Subcluster A1 includes several Southern and Eastern European nations, such as Croatia, Greece, Italy, Spain, and Romania, that have lower levels of enterprise AI integration and fewer science and technology professionals. Despite these limitations, their sustainability performance remains relatively consistent, indicating that environmental and social results do not necessarily advance alongside digital and economic growth. This pattern underscores a structural setup in which AI adoption and high-skilled labor lag, while broader policy contexts influence sustainability outcomes.

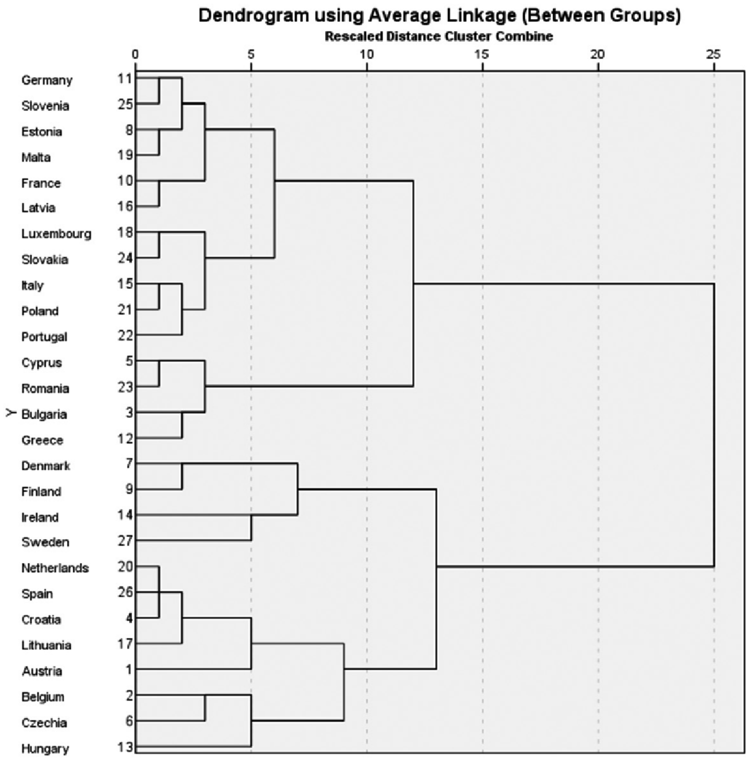

Figure 1. Dendrogram

Subcluster A2 represents a transitional group comprising Central and Eastern European countries, as well as some Western economies such as France and Ireland. These nations demonstrate higher levels of AI adoption, robust employment rates, and a growing share of science and technology professionals. The grouping suggests that these economies are gradually evolving towards greater digital maturity, underscoring the critical role of improved human capital and institutional support in fostering AI-led structural change.

Cluster B encompasses countries with advanced digital ecosystems and strong institutional foundations. Subcluster B1 includes Austria, Germany, Slovenia, and Malta, all of which have high GDP per capita, strong scientific sectors, and active sustainability initiatives. Subcluster B2 features Europe's digital frontrunners, including Sweden, Finland, Denmark, the Netherlands, and Belgium, where AI adoption, human capital, and sustainability results consistently lead the way. Luxembourg is notable for its exceptional economic performance but has comparatively weaker sustainability efforts, highlighting that wealth alone does not ensure comprehensive development.

Importantly, although these clusters correspond to established regional patterns within the EU, their main contribution is to illustrate how task-based technological change varies across different institutional and developmental contexts. The clustering findings substantiate the results of the EFA and GLM analyses by highlighting that AI adoption is most associated with configurations featuring high-skilled labor and supportive institutions. Thus, the cluster analysis supports Hypothesis H3 by showing how similarities in AI readiness, labor market structure, economic performance, and sustainability outcomes lead to meaningful national groupings, rather than revealing new regional splits.

5. Discussion

This study's findings contribute to the growing body of empirical research on AI by showing how AI adoption is linked to broader socio-economic and sustainability frameworks across EU countries. Rather than uniform effects, the results suggest that AI adoption tends to be associated with specific labor market structures, levels of economic performance, and sustainability outcomes.

Regarding labor market dynamics, the consistent link between AI adoption and the share of workers in science and technology fields supports task-based models of technological change. In line with the work of Autor (2015) and Acemoglu and Restrepo (2020), the findings suggest that AI adoption is more closely associated with the reassignment of tasks to cognitively intensive, technology-enhanced activities than with overall employment changes. Recent empirical evidence supports this, showing that AI is associated with employment growth in knowledge-intensive sectors, especially in regions with strong technological infrastructure and effective education systems (Liang et al., 2025). Evidence from newer EU member states also suggests that AI can foster positive structural shifts even amid ongoing economic transformation (Guliyev, 2023; Necula et al., 2024; Chemlal & Benomar, 2024).

The modest link between AI adoption and overall employment underscores the nuanced relationship between AI and labor markets. Consistent with Bessen et al. (2020) and Acemoglu and Restrepo (2019), the findings indicate that AI is not consistently associated with widespread employment growth. Instead, employment outcomes appear to hinge on how well AI complements existing skills and on how public policies shape labor-market adjustments.

The second set of findings, linking AI adoption to economic performance and sustainability, underscores the importance of context in digital transformation. The correlations among AI use, GDP per capita, and SDG index scores align with prior research showing that AI is positively associated with Europe's economic performance (Kalai et al., 2024). Additional evidence comes from studies that emphasize AI's role in boosting productivity, particularly in innovation-driven, flexible sectors (Graetz & Michaels, 2018; Damioli et al., 2021).

Regarding sustainability, the observed positive link between AI adoption and SDGi scores indicates that digital technologies are associated with progress toward Sustainable Development Goals, improving resource efficiency and energy management (Sun et al., 2025). Nonetheless, as the literature notes, these advantages are conditional and may be undermined by rebound effects or by increased social inequalities if not managed effectively (Dauvergne, 2021; Almusharraf, 2025). Recent studies highlight that the sustainability impact of AI depends not only on technological advances but also on policy decisions and institutional coordination (Badulescu et al., 2024; Pimenow et al., 2025; Zhou, 2025).

Cluster analysis helps describe the relationships among AI adoption, labor market structure, economic performance, and sustainability by revealing how countries develop distinct profiles. Although the clusters align with known regional patterns within the EU, their primary value is in illustrating how task-based technological changes unfold differently across institutional and developmental settings. Previous regional studies (Sompolska-Rzechuła, 2020; Mura & Donath, 2023) support the view that variations in digital infrastructure, innovation capacity, and education policies continue to shape diverse AI-related paths among EU member states.

5.1. Policy implications

This study suggests that AI policies should be integrated into broader, coordinated strategies that prioritize the development of human capital, strengthen institutions, and promote sustainability. The link between AI adoption and the share of highly skilled workers in science and technology underscores the importance of education, vocational training, and lifelong learning to help workers complement AI technologies rather than be displaced by them. Targeted reskilling and upskilling are especially crucial in regions with slower digital adoption and larger skill gaps.

At the same time, the link between AI adoption and economic performance shows that digital transformation efforts work best when supported by strong innovation ecosystems and solid digital infrastructure. Investing in R&D, encouraging technology adoption among small and medium-sized enterprises, and improving digital access can ensure that AI adoption is associated with broader economic gains rather than being limited to a few firms or sectors.

The sustainability results underscore the importance of aligning AI strategies with environmental and social policies. While AI can improve sustainability outcomes, these benefits are not automatic and can be undermined by weak governance. Integrating AI into policies focused on energy efficiency, green innovation, and social inclusion can help mitigate risks and promote balanced development.

Overall, the diverse patterns across EU member states indicate that AI policies should be customized to local contexts, taking into account digital maturity, human capital, and institutional strength. This customized approach can foster more inclusive and sustainable AI adoption across the European Union.

5.2. Limitations and further research

This study provides a cross-sectional comparison of how AI adoption relates to employment structures, economic outcomes, and sustainability across EU member states.

Several limitations should be noted. First, the analysis uses a small sample size restricted to EU countries, which ensures comparability but limits statistical power and the ability to extend findings beyond the EU. Furthermore, relying on aggregated national indicators prevents the examination of more detailed differences at regional, sectoral, or firm levels.

Second, the limitations of the exploratory factor analysis include the small number of variables per model and borderline KMO values. Therefore, factor extraction should be seen mainly as an exploratory tool for identifying patterns of co-variation, not for defining strong latent constructs. Future research can improve on this with richer datasets, enabling more detailed multivariate analysis.

Third, the cross-sectional approach limits interpretation to current associations and does not allow full control for endogeneity or omitted-variable bias. EU-level data on enterprise AI adoption, relevant to labor markets, economic factors, and sustainability, are available only for 2023–2024. This restricts the use of longitudinal or panel data analysis, so causal inference and evaluation of dynamic effects are not covered in this study.

Finally, the empirical framework does not explicitly handle endogeneity, reverse causality, or omitted-variable bias. It also overlooks qualitative factors such as institutional quality, governance structures, and societal attitudes toward AI. As longer time series and more detailed data become available, future research could use panel econometric methods, include additional explanatory variables, and adopt mixed-method approaches to gain a more complete understanding of AI-related changes.

6. Conclusions

This study shows that artificial intelligence operates within a broader ecosystem shaped by human skills, institutions, and policy choices, rather than being a primary driver of change in and of itself. Countries with strong education systems, robust digital infrastructure, and supportive innovation environments tend to benefit most, as AI is associated with stronger economic performance and a larger share of scientific talent and technical talent without triggering significant job losses. It is also associated modestly with progress toward sustainability goals, suggesting that AI can fit within Europe's vision of greener, more inclusive growth.

At the same time, the study highlights uneven progress across the European Union. National differences in digital readiness and sustainable development underscore the need for policies that reflect each country's unique context rather than relying on uniform solutions. Strengthening AI's contribution to development requires a mix of forward-looking strategies that help workers adapt, reinforce ethical and transparent governance, and support regions lagging in digitalization or innovation capacity. These efforts would amplify AI's positive impact while encouraging more balanced, resilient growth.

Our findings prompt a wider reflection on Europe's approach to integrating AI into its economic and social systems. AI by itself cannot transform societies; this transformation depends on thoughtful, inclusive choices made by European institutions, labor markets, and communities.

Given the cross-sectional design of this study, endogeneity and omitted variable concerns cannot be fully addressed. Future research could extend this analysis using panel data and dynamic approaches to better capture temporal patterns and strengthen the robustness of the observed associations.

Author contributions

The authors contributed equally to this paper.

Disclosure statement

The authors do not have any competing financial, professional, or personal interests from other parties.

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APPENDIX

Table A1. Clusters data

Country	AI	EMPL	HRST	GDPpc	SDGi
Croatia	11.76	70.8	23.5	76	72.4
Spain	11.31	70.5	23.6	91	71.2
Greece	9.81	67.4	21.0	69	66.5
Italy	8.20	66.3	17.3	98	72.3
Romania	3.07	68.7	16.2	78	64.2
Subcluster A1 mean	8.83	68.74	20.32	82.40	69.32
Latvia	8.83	77.5	23.8	70	70.6
Portugal	8.63	78.0	22.5	81	70.6
Bulgaria	6.47	76.2	21.9	64	62.9
Hungary	7.41	80.7	22.7	77	68.8
Czechia	11.26	81.7	20.0	90	73.7
Slovakia	10.78	77.5	19.4	74	70.6
Cyprus	7.90	79.5	30.1	97	62.7
Lithuania	8.76	78.5	29.6	87	67.8
Poland	5.90	77.9	27.4	77	73.3
France	9.91	74.4	29.2	99	73.9
Estonia	13.89	82.1	26.0	80	71.7
Ireland	14.90	79.1	30.7	213	71.5
Subcluster A2 mean	9.55	78.59	25.28	92.42	69.83
Cluster A mean	9.34	75.69	23.82	89.47	69.68
Austria	20.27	77.2	23.6	120	77.3
Slovenia	20.89	77.5	25.7	92	73.8
Germany	19.75	81.1	22.9	116	75.0
Malta	17.30	81.3	20.0	107	69.3
Subcluster B1 mean	19.55	79.28	23.05	108.75	73.87
Denmark	27.58	79.8	30.4	125	79.7
Finland	24.37	78.2	30.4	105	81.1
Netherlands	23.06	83.5	30.3	133	71.9
Sweden	25.09	82.6	34.2	114	79.4
Belgium	24.71	72.1	31.6	118	72.2
Subcluster B2 mean	24.96	79.24	31.38	119.00	76.85
Luxembourg	23.73	74.8	45.4	237	67.6
EU mean	14.28	76.85	25.90	103.26	71.55