

The Drivers of Artificial Intelligence Adoption in the European Union: A Three-Level Digital Divide Perspective

Erika Seres Huszárík¹ and Viktor Busánszki^{1*}

¹Faculty of Economics and Informatics, J. Selye University, Slovakia

*Correspondence: 121727@student.ujs.sk

PAPER INFO

Paper history:

Received 07 May 2026

Accepted 11 October 2026

Citation:

Seres Huszárík, E., & Busánszki, V. (2026). The drivers of artificial intelligence adoption in the European Union: A three-level digital divide perspective. In *Journal of Information and Organizational Sciences*, vol. 50, no. 2, pp. 309-323

Copyright:

© 2026 The Authors. This work is licensed under a Creative Commons Attribution BY-NC-ND 4.0. For more information, see <https://creativecommons.org/licenses/by-nc-nd/4.0/>

ABSTRACT

This study examines the macro-level factors associated with artificial intelligence (AI) adoption among enterprises in the European Union through the three-level digital divide framework. Despite the EU's Digital Decade 2030 targets, AI integration remains limited and uneven across member states. Using 2024 Eurostat data for the EU27, the study applies OLS multiple linear regression and exploratory K-means clustering to examine the relationships between broadband infrastructure, ICT skills, enterprise digital intensity, and AI usage. Enterprise digital intensity shows the strongest positive statistical association with AI adoption, whereas the coefficients for ICT specialists and broadband are not statistically significant in the multivariate model. A leave-one-country-out analysis indicates that the positive DII association is not driven by any single member state. The cluster analysis identifies three distinct country profiles based on their digital characteristics. The findings suggest that infrastructure alone may be insufficient to account for cross-country variation in AI adoption and that broader organizational digital maturity should also be considered. Given the cross-sectional design, the results are interpreted as associations rather than causal effects.

Keywords: Artificial intelligence, Digital divide, European Union

1. Introduction

Artificial intelligence (AI) has unequivocally established itself as one of the most defining technologies for 21st-century corporate competitiveness and innovation. Recognizing this paradigm shift, the European Union established the Digital Decade 2030 program, setting an ambitious goal: by the end of the decade, 75% of European enterprises should integrate artificial intelligence, cloud computing, or big data analytics into their daily operations (Decision (EU) 2022/2481, 2022).

Macroeconomic data, however, present a concerning picture: in 2024, an average of only 13.48% of EU enterprises deployed any form of AI technology (Eurostat, 2026). Furthermore, drastic differences of up to ninefold can be observed between the leading and lagging member states. This slow and heterogeneous adoption highlights that the technological transition is not an automatic process, and the European economy risks becoming increasingly fragmented along digital lines.

To better understand this phenomenon and inform the discussion of potential policy responses, it is necessary to move beyond a purely infrastructural perspective. The theoretical framework of this study is built on the perspective of the three-level digital divide, which makes a clear distinction between physical access to technology, the human skills required for usage and implementation, and the outcomes achieved through the integration of digital technologies (Deursen & Helsper, 2015). Adapting this model to a corporate

context provides a much more nuanced picture of why the development of many regions stalls despite adequate infrastructure.

This study contributes to the digital divide literature by refining the three-level framework for the macro-level analysis of enterprise AI adoption. Rather than viewing access, skills, and advanced technology use as an automatic linear sequence, it conceptualizes them as complementary but unevenly developed dimensions. The findings highlight a potential configuration gap: countries may possess extensive infrastructure or specialized human capital without translating these resources into widespread AI use. Enterprise digital intensity is therefore interpreted as an indicator of organizational readiness to combine digital resources and embed them in business processes. Accordingly, the study shifts attention from the availability of individual digital resources to the capacity of enterprises to convert complementary resources into advanced technology use.

2. Literature Review

Artificial intelligence has become a disruptive technology for corporate value creation, fundamentally changing business models (Åström et al., 2022). Although the European Union has an ambitious goal for most companies to integrate the technology by 2030, adoption is currently extremely slow and heterogeneous across member states. The literature describes this phenomenon as the productivity paradox (Andrews et al., 2016). The essence of the paradox is that despite the existence of advanced technologies, the general productivity of the economy is not increasing at the expected rate, primarily due not to the performance of top-tier companies, but rather the highly asymmetrical and slow diffusion of innovations among smaller market players (SMEs) (Andrews et al., 2016; OECD, 2023).

To understand the causes of slow corporate adoption, we must move beyond the idea that mere physical access to technologies automatically results in innovation. To comprehensively explain the inequalities, we use the three-level digital divide theoretical model developed by Dijk (2020), where:

Primary divide (access and infrastructure): Refers to physical access to technology (Riggins & Dewan, 2005). Empirical research, however, sharply highlights the broadband paradox, which means that although the existence of infrastructure is essential, it is by no means a sufficient condition for technological innovation and AI adoption on its own (Gallardo et al., 2018; Laitso et al., 2025). Infrastructure alone does not guarantee the spread of AI, as seen in Romania, which has one of the highest VHCN coverage rates in the EU, yet paradoxically exhibits one of the lowest proportions of enterprises using AI (Laitso et al., 2025).

Secondary divide (skills and usage): Due to the complexity of software and data, inequality is now defined by the lack of digital competencies (Deursen & Dijk, 2010). Skill-biased technological change elevates the role of ICT specialists within organizations. In the EU, a large portion of companies identifies the very lack of internal expertise as the main barrier to AI adoption (Eurostat, 2025a).

Tertiary divide (outcomes and strategic advantages): The latest scientific focus goes beyond mere usage to actual strategic benefit (Deursen & Helsper, 2015). As defined by Ragnedda (2017), this level measures how existing digital capital can be converted into real economic results. In the case of AI, this means that technologically more mature companies reap exponentially greater benefits from innovation, further worsening the competitive position of those starting from a disadvantage (Calderon Gomez, 2021).

Research examining AI integration suggests that adoption is not an isolated event but is associated with several complementary organizational and environmental factors:

Enterprise Digital Intensity: Calvino and Fontanelli (2023) and Babina et al. (2024) point out that AI adoption is closely related to the company's existing organizational intangible assets and general digital maturity. The integration of cloud-based systems and IoT creates the structured data environment required for AI algorithms to learn effectively.

Specialist Shortage: Accelerated technological development has extremely increased the demand for AI competencies. Since 78% of general ICT jobs now require some level of AI technical knowledge (AI-Enabled ICT Workforce Consortium, 2024), the unequal global and intra-regional distribution of human capital (World Bank, 2024) is a critical barrier to corporate adoption.

Regulatory and Environmental Constraints: Beyond physical constraints, by 2024, the lack of clarity regarding legal consequences (e.g., EU AI Act compliance obligations), data privacy concerns, and massive implementation costs emerged as major barriers (Ionascu, 2025; Gualandri & Kuzior, 2024). For this reason, company size is one of the most robust macro-level predictors, as the proportion of well-capitalized large corporations significantly determines a national economy's AI integration rate (Laitso et al., 2025).

Previous research does not provide a fully consistent explanation of enterprise AI adoption. Infrastructure oriented studies emphasize broadband access as a necessary foundation, yet evidence from digitally connected countries suggests that connectivity alone does not ensure advanced technology use. Skills based research

identifies specialized expertise as a central barrier, while studies of organizational digital maturity place greater emphasis on complementary assets, established digital processes, and data resources. These perspectives are not necessarily contradictory, but they differ in which dimension they treat as the principal constraint. Moreover, the literature often examines infrastructure, skills, and organizational maturity separately, leaving their relative importance and joint relationships unclear. The present study positions itself within this debate by examining the three dimensions in a common empirical framework. It interprets enterprise AI inequality as a conversion problem in which the availability of individual digital resources does not necessarily coincide with the organizational capacity to combine them and translate them into advanced technology use.

3. Materials and Methods

This study applies a quantitative, cross-sectional research design to examine the factors associated with AI adoption across EU member states. The analytical framework is built on the three-level digital divide perspective, which distinguishes between access to technology, skills needed for usage, and outcomes achieved through digital technologies. We adapted this theoretical framework to a corporate context to examine macro-level differences in AI diffusion.

The empirical analysis focuses on the year 2024, using Eurostat's annual database examining ICT usage by European enterprises. In line with Eurostat's standard sampling frame, the research is limited to enterprises employing at least 10 people. This delimitation not only guarantees comparability across EU member states but is also professionally justified, as digital practices and the organizational application of AI can be more reliably identified in larger companies. The final analytical sample consists of 27 observations, corresponding to the EU member states, and contains no missing data for the included variables.

3.1. Variables and Operationalization

The selection of the three explanatory variables was guided by their correspondence with the principal dimensions of the adapted digital divide framework, their availability for all EU member states in the same reference year, and their harmonized measurement by Eurostat. This theoretically grounded and parsimonious specification was also appropriate for the limited sample of 27 member states. The selected variables represent access, specialized skills, and organizational digital readiness, but they are not intended to provide an exhaustive account of all factors associated with AI adoption.

<i>Theoretical Dimension</i>	<i>Construct in Enterprise Context</i>	<i>Empirical Proxy (Eurostat 2024)</i>	<i>Theoretical Rationale</i>
1. Primary Divide (Access)	Physical and infrastructural availability of advanced networking.	Broadband Infrastructure (broadband_100mb_pct)	High-speed connectivity is the baseline prerequisite for data-intensive cloud computing and AI training/operation.
2. Secondary Divide (Skills)	Internal specialized capabilities required to manage and integrate complex technologies.	Specialized Human Capital(ict_specialists_pct)	AI solutions rarely function as plug-and-play tools; they demand algorithmic, data structuring, and prompt-design competencies.
3. Tertiary Divide (Outcomes / Readiness)	Organizational capacity to translate digital tools into embedded business processes.	Enterprise Digital Intensity(dii_basic_pct)	Rather than a final economic outcome, DII is operationalized here as the necessary organizational digital maturity (readiness) bridging basic IT use and advanced AI outcomes.

Table 1. Variables measuring artificial intelligence adoption and digital divide dimensions in the EU 27

Dependent Variable: Percentage of enterprises using AI (*ai_use_pct*): This ratio captures the percentage of companies in a given member state that apply at least one AI technology in their business operations.

Independent Variables (by digital divide dimensions): (1) **Access Dimension:** The proportion of enterprises with a broadband connection of at least 100 Mb/s (*broadband_100mb_pct*). Operating AI solutions requires high-capacity infrastructure, so this can be interpreted as a substantive structural condition.

(2) **Skill Dimension:** Covers the proportion of enterprises employing ICT specialists (*ict_specialists_pct*). This variable indicates the presence of specialized internal expertise, which is essential for knowledge-intensive AI adoption.

(3) **Organizational Digital-Use Dimension:** The proportion of enterprises with at least basic digital intensity (*dii_basic_pct*). The Digital Intensity Index (DII) is a composite Eurostat indicator; the "basic level" means the enterprise has integrated at least four of the 12 examined digital technology solutions. This indicator captures the general maturity of enterprise digitalization and is interpreted here as organizational readiness for more advanced technology use rather than as a final tertiary outcome. As DII and AI use both reflect aspects of enterprise digital transformation, we acknowledge a potential conceptual and empirical overlap between the two constructs. Therefore, DII is treated strictly as a statistical proxy for organizational digital readiness rather than as a strictly exogenous determinant of AI adoption.

To clarify the theoretical correspondence between the chosen empirical variables and the adopted three-level digital divide framework, Table 1 presents the conceptual mapping of the constructs.

3.2. Analytical Procedures

The statistical analysis of the data was performed using the SPSS statistical software package in four sequential steps:

First, descriptive statistics were applied to assess the heterogeneity of the variables across member states.

Second, the bivariate relationships between the dependent and explanatory variables were examined. Due to the small sample size ($N=27$) and the limited fulfillment of distribution assumptions for parametric tests, the more robust, non-parametric Spearman rank correlation was used. To examine the conditional relationships between the selected indicators and AI adoption, a multiple linear regression model was estimated. To address potential heteroscedasticity and provide a more transparent assessment of statistical uncertainty given the small country-level sample ($N=27$), the model was estimated using heteroscedasticity-robust standard errors (HC3), and 95% confidence intervals are reported alongside p-values. The econometric validity of the model was verified with detailed diagnostics: the distorting effect of multicollinearity was excluded (all VIF values < 2.5), and a leave-one-country-out analysis confirmed that the coefficients were not disproportionately influenced by any individual country. Because the data are cross-sectional and observational, the estimated coefficients are interpreted as conditional associations and not as causal effects.

Third, the model's performance was evaluated using the degrees-of-freedom adjusted coefficient of determination (Adjusted R^2), taking into account the number of predictors relative to the sample size, and an F-test.

As a fourth, exploratory step, a K-means cluster analysis was performed using broadband availability, ICT specialist employment, and basic digital intensity. Alternative solutions containing two to six clusters were compared using the silhouette coefficient, the Calinski-Harabasz index, and the Davies-Bouldin index (the full validation statistics for $k=2$ to $k=6$ are provided in Appendix A). Although the two-cluster solution showed the strongest numerical validation, the three-cluster solution was retained because it distinguished a substantively important transitional profile and provided a more informative representation of differences among EU member states. Furthermore, to address the potential bias arising from the unequal dispersion of variables measured on a percentage scale, a robustness test using standardized Z-scores was performed to verify the stability of the classification.

4. Results

The presentation of this research's results is based on the theoretical framework of the three-level digital divide, structured in four sequential phases. The analysis examines the macro-level relationships between the selected digital indicators and corporate artificial intelligence adoption across EU member states.

4.1. Macro-Level Digital Development

As a first step of the data analysis, the distribution and variance of the included variables were examined, which in itself paints a very telling picture of the digital divide in the European corporate sector. Descriptive

statistics point out that despite the European Union's unified market vision, marked differences remain across individual member states. The statistical data of our variables are illustrated in Table 2.

	ai_use_pct	dii_basic_pct	ict_specialists_pct	broadband_100mb_pct
N Valid	27	27	27	27
Missing	0	0	0	0
Mean	14,2793	72,3322	20,3359	64,8630
Median	11,3100	71,8500	19,2200	63,3600
Mode	3,07 ^a	50,94 ^a	11,27 ^a	42,32 ^a
Std. Deviation	7,17728	10,19859	6,15603	14,35366
Variance	51,513	104,011	37,897	206,028
Minimum	3,07	50,94	11,27	42,32
Maximum	27,58	92,76	32,43	90,16
a. Multiple modes exist. The smallest value is shown.				

Table 2. Variables measuring artificial intelligence adoption and digital divide dimensions in the EU 27 member states (2024)

The dependent variable of the research, the proportion of companies integrating at least one AI technology into their business processes (ai_use_pct), varies widely across EU member states. Based on the statistical analysis, the average adoption rate of the 27 countries in the sample is 14.28%. This indicator is in close alignment with Eurostat's macro-level reports, stating that in 2024 about 13% of European businesses used some AI technology (Eurostat, 2025b). This seemingly modest adoption rate projects a worrying picture for the European Union's global competitiveness, especially since one of the main objectives of the "Digital Decade 2030" program is for 75% of EU companies to integrate AI, cloud computing, or big data analytics by the end of the decade. The current average adoption of around 14% means the European economy is lagging significantly, and at the current growth rate, estimates suggest that by 2030, only 17-20% of companies will reach meaningful AI use at best (European Commission, 2024a).

The distribution of the dependent variable is asymmetrical. The 14.28% average is accompanied by a significantly lower median of 11.31%, indicating a positively skewed distribution. This distribution shape indicates that most member states perform below the already low EU average, with the mean being pulled up by a narrow, highly developed group of states. The outstanding variance value of 51.51 and the standard deviation of 7.18 percentage points are clear evidence of macro-level division. At the top end of the scale are Denmark (27.58%), Sweden (25.09%), Belgium (24.71%), and Finland (24.37%). These Scandinavian and Western European states represent the continent's technological vanguard. In sharp contrast, at the lower end of the spectrum is Romania, where the proportion of AI-using companies is only 3.07%, followed by Poland (5.90%), Bulgaria (6.47%), Hungary (7.41%), and Cyprus (7.90%). The nearly ninefold difference between the best (Denmark) and worst (Romania) performing member states highlights that Europe remains deeply divided along the digital divide.

Based on the research's theoretical framework, a descriptive analysis of three explanatory variables operationalizing the dimensions of digital access, skills, and usage was conducted.

The proportion of enterprises with at least basic digital intensity (dii_basic_pct) has the highest average in the sample. The Digital Intensity Index (DII) measures whether a company uses at least four of the examined basic digital technologies (e.g., e-commerce, social media, enterprise resource planning systems). The EU average in this regard is 72.33%, and the median is 71.85%, indicating a relatively symmetrical structure approaching normal distribution. The variable's standard deviation is 10.20 percentage points, showing less heterogeneity than AI usage. Although the European Union has, at the aggregate level, moved closer to the 2030 Digital Decade target, which states that over 90% of SMEs should reach basic digital intensity, while the current state is around 73% in the entire corporate population, the data draw attention to a crucial point (Eurostat, 2025b). In most member states, the majority of companies were able to reach the basic digitalization threshold (92.76% in Finland, 90.76% in Denmark, 87.02% in Sweden, but even in weaker-performing countries, the rate exceeds 40%), but this digitalization process did not automatically mean advanced technological maturity.

Human capital preparedness is captured by the proportion of companies employing ICT specialists (ict_specialists_pct). Its average value is 20.34% (median: 19.22%), with a relatively moderate standard deviation of 6.16 percentage points. The theoretical relevance of the variable comes from the fact that integrating AI is rarely achieved by simply purchasing ready-made products; in the vast majority of cases, it requires internal engineering, data analysis, or prompt-design knowledge. This is supported by surveys: 70.89% of European companies that considered introducing AI technologies but ultimately rejected it cited the lack of relevant expertise as the primary cause of failure (Eurostat, 2025a). Macro data also confirm this structural barrier: in 2024, only about 10.3 million people worked as ICT specialists in the EU, critically falling short of the 20 million target set for 2030 by nearly 10 million people (Eurostat, 2025b). In this field, Malta (32.43%), Denmark (29.07%), Ireland (28.71%), and the Netherlands (27.69%) lead the pack, while Italy (11.27%), Romania (11.70%), Spain (12.88%), and Lithuania (14.10%) struggle with serious human resource deficits. Interestingly, Hungary performs surprisingly well in this area (27.72%), significantly exceeding the EU average, but as the regression analysis later shows, this knowledge capital alone was not sufficient for outstanding AI adoption.

The access dimension is given by broadband infrastructure availability, which is the proportion of enterprises with at least a 100 Mb/s internet connection (broadband_100mb_pct). This variable shows the highest variance (206.03) and standard deviation (14.35) in the examined set. The EU average is 64.86%, but values range between extreme limits. Denmark (90.16%), Cyprus (83.53%), Romania (82.56%), and Spain (80.23%) top the infrastructure list. EU policy reports also note that optical networks reach only 64% of households and businesses, and high-quality 5G coverage extends to only 50% of the EU's territory (European Commission, 2024b; European Commission, 2024c). Surprisingly, among the laggards are industrialized Germany (64.71%), as well as countries struggling with infrastructural challenges like Croatia (42.32%), Greece (43.64%), Czechia (45.99%), and Slovakia (46.73%). These drastic infrastructure differences indicate that EU member states have pursued different national network development strategies over the past decade, significantly influencing the availability of bandwidth essential for data intensive applications, cloud services, and the operation of AI systems.

The descriptive statistics validate the rationale of the study. The substantial variance among member states, both in AI adoption and in infrastructural and skill-related endowments, indicates a heterogeneous macro-environment that justifies and enables the application of more in-depth, multivariate econometric regression models.

4.2. Direct Relationships of Artificial Intelligence Adoption

		ai_use_pct	dii_basic_pct	ict_specialists_pct	broadband_100mb_pct
ai_use_pct	Correlation Coefficient	1,000	,656**	,421*	0,222
	Sig. (2-tailed)		0,000	0,029	0,265
dii_basic_pct	Correlation Coefficient	,656**	1,000	,526**	,711**
	Sig. (2-tailed)	0,000		0,005	0,000
ict_specialists_pct	Correlation Coefficient	,421*	,526**	1,000	0,297
	Sig. (2-tailed)	0,029	0,005		0,132
broadband_100mb_pct	Correlation Coefficient	0,222	,711**	0,297	1,000
	Sig. (2-tailed)	0,265	0,000	0,132	
** Correlation is significant at the 0.01 level (2-tailed).					
* Correlation is significant at the 0.05 level (2-tailed).					

Table 3. Spearman Rank Correlation Coefficients

To uncover the relationships between digital indicators, correlation calculations were performed in the second step. Due to the relatively small sample size ($N = 27$ member states) and the fact that the distribution of the variables in several cases (especially the dependent variable) deviates from normal distribution, the more robust non-parametric Spearman rank correlation was used instead of the parametric Pearson correlation, the results of which are shown in Table 3.

The strongest statistically significant positive relationship can be demonstrated between the proportion of enterprises using AI (*ai_use_pct*) and the proportion of enterprises with at least basic digital intensity (*dii_basic_pct*) ($r_s = 0.656$, $p < 0.001$). This association is consistent with the view that general digital maturity and advanced technology use are closely related, while not necessarily forming an automatic linear sequence. In the operating environment of European companies, AI does not exist in a vacuum. As European Commission data also highlight, effective AI application is closely correlated with sophisticated cloud services (currently used by 39% of EU SMEs) and advanced data analytics solutions (33%) (Eurostat, 2025b). The Digital Intensity Index (DII) precisely measures the presence of these fundamental building blocks. The results suggest that economies with less widespread use of enterprise resource planning systems, customer relationship management software, and digital databases also tend to display lower levels of AI adoption. These technologies may represent elements of the broader digital environment associated with advanced technology use.

Examining the human capital dimension yields similarly remarkable results. A statistically significant moderate positive relationship can be identified between the proportion of companies employing ICT specialists (*ict_specialists_pct*) and AI usage ($r_s = 0.421$, $p = 0.029$). This association is consistent with the relevance of specialized internal knowledge for AI adoption, although it does not establish a causal effect. The European corporate introduction of artificial intelligence typically requires in-house, custom developments or fine-tuning, especially in the information and communication sector (where AI adoption is 62.52%) and in professional scientific and technical services (40.43%) (Eurostat, 2025a).

The most surprising discovery of the correlation analyses, however, relates to the technological infrastructure. The Spearman rank correlation showed only a weak, and more importantly, statistically non-significant relationship between the presence of a connection of at least 100 Mb/s bandwidth (*broadband_100mb_pct*) and the corporate application of AI ($r_s = 0.222$, $p = 0.265$). To understand the apparent ineffectiveness of bandwidth, the intercorrelations between explanatory variables must be examined. Although bandwidth itself does not correlate directly with AI usage, it has an extremely strong, significant positive relationship with basic digital intensity (DII) ($r_s = 0.711$, $p < 0.001$). High speed broadband availability alone does not necessarily coincide with widespread AI adoption. Its strong positive correlation with DII is consistent with the interpretation that connectivity is more closely related to general enterprise digitalization than directly to AI adoption. However, the cross sectional correlations do not establish the direction or causal ordering of these relationships.

Understanding this is critical for the allocation of EU funds. From a policy perspective, the descriptive pattern observed in countries such as Romania, Spain, and Cyprus suggests that extensive broadband availability does not necessarily coincide with high levels of enterprise AI adoption. These cases are consistent with the possibility that connectivity needs to be complemented by organizational digitalization and related capabilities. Nevertheless, the present analysis does not establish that infrastructure investment without such complementary measures causes lower or slower AI adoption.

4.3. Multiple Linear Regression Model

The model shows a relatively strong in-sample fit, although the estimates must be interpreted cautiously given the small country-level sample. The multiple correlation coefficient ($R = 0.774$) indicates a strong joint relationship, while the coefficient of determination ($R^2 = 0.599$) shows that the three independent variables explain about 60% of the variance of the dependent variable (AI usage), as illustrated in Table 4.

R	R Square	Adjusted R Square	Std. Error of the Estimate
.774 ^a	0,599	0,547	4,83196

Table 4. Regression Model Results

Given the relatively small sample size ($N = 27$), the adjusted R-squared must be considered the guiding metric when evaluating model performance. Its value of 0.547 indicates that the included variables account for approximately 55% of the observed cross-country variation in AI adoption within the analyzed sample. The

overall statistical significance of the model is supported by the F-test performed within the ANOVA framework ($F = 11.455, p < 0.001$).

An essential condition for the model's validity is ruling out multicollinearity among predictors. The analysis of variance inflation factors yielded satisfactory results: the VIF value for DII was 2.38, for ICT specialists 1.30, and for broadband 2.11. Since all values remained below the critical threshold of 5, it can be stated that although the independent variables correlate with each other, they do not carry enough redundant information to make the estimation of regression coefficients unstable and increase standard errors.

The unstandardized (B) coefficients with heteroscedasticity-robust standard errors (HC3), standardized coefficients (β), and 95% confidence intervals indicate the direction, relative strength, and statistical precision of the conditional associations with AI adoption, as shown in Table 5.

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95% Confidence Interval	
	B	Robust Std. Error				Lower	Upper
1 (Constant)	-23,979	6,207		-3,863	0,000	-36,145	-11,813
dii_basic_pct	0,620	0,150	0,881	4,120	0,000	0,325	0,914
ict_specialists_pct	0,205	0,164	0,176	1,248	0,212	-0,117	0,526
broadband_100mb_pct	-0,165	0,107	-0,331	-1,541	0,123	-0,376	0,045

Table 5. Analysis of Unstandardized (B) and Standardized (Beta) Coefficients with Robust Standard Errors

In the multidimensional space, while controlling for the other two variables, basic digital intensity (*dii_basic_pct*) emerges as the strongest and most statistically reliable correlate of AI adoption among the included predictors. According to the mathematical interpretation of the unstandardized regression coefficient ($B = 0.620, p < 0.001, 95\% \text{ CI } [0.325, 0.914]$), holding the other included variables constant, a one-percentage-point difference in corporate digital intensity is associated with an estimated 0.62-percentage-point difference in the proportion of enterprises using AI. Based on the standardized coefficient ($\beta = 0.881$), the relative weight of the DII far exceeds all other examined factors. The partial correlation of 0.571 indicates a comparatively strong conditional relationship between DII and AI adoption after accounting for the other included predictors. Higher AI adoption is observed primarily in countries where broader digital practices, including cloud use, data analysis, and e-business software, are also more widespread.

The negative constant ($B = -23.979, p < 0.001, 95\% \text{ CI } [-36.145, -11.813]$), has limited substantive interpretation because zero values on all three predictors lie outside the observed data range.

The coefficient for ICT specialists is positive but not statistically significant after controlling for DII and broadband ($B = 0.205, p = 0.212, 95\% \text{ CI } [-0.117, 0.526]$). Its weaker conditional association may partly reflect the positive correlation between ICT employment and general digital intensity. However, the present model does not test whether DII mediates the relationship between specialized human capital and AI adoption. The result therefore indicates only that the ICT-specialist variable provides limited additional explanatory information once the other included predictors are held constant.

The broadband coefficient is negative but does not reach the conventional 5% significance level ($B = -0.165, p = 0.123, 95\% \text{ CI } [-0.376, 0.045]$). This conditional coefficient differs in sign from the weak positive bivariate correlation between broadband and AI use, showing that the estimated relationship changes when DII and ICT employment are included in the model. If we assume two EU member states with exactly the same level of enterprise digital intensity and the same proportion of enterprises employing ICT specialists, the model suggests that AI adoption may be lower in the country where broadband availability is disproportionately higher. One possible interpretation is that some countries have developed extensive broadband infrastructure without achieving a corresponding level of organizational digital transformation. This pattern is visible in countries such as Romania and Cyprus, where broadband coverage exceeds 80%, while AI adoption remains comparatively low. In these cases, investments in physical connectivity may have outpaced the diffusion of advanced digital practices and business-process transformation. From this perspective, extensive connectivity appears to be a necessary but not sufficient condition for advanced technology adoption. This interpretation is broadly consistent with OECD observations that narrowing broadband connectivity divides alone is unlikely to eliminate wider digital transformation gaps across firms and regions (OECD, 2025). However, the coefficient does not establish a negative causal effect of broadband

or provide conclusive evidence of a suppressor mechanism, and should therefore be interpreted as a statistically uncertain conditional association requiring further investigation.

The leave-one-country-out analysis supported the stability of the principal result. The DII coefficient remained positive and statistically significant across all 27 specifications and varied within a relatively narrow range ($B = 0.566\text{--}0.699$). The coefficient for ICT specialists remained positive but non-significant in every specification. The broadband coefficient remained negative across all specifications but reached the 5% significance level in only one case. Thus, no individual member state altered the central finding concerning the positive association between DII and AI adoption.

4.4. Country-Level Residual Patterns

The country-level residuals identify member states whose observed AI-adoption rates differ comparatively strongly from the values fitted by the model. These deviations may indicate omitted country characteristics, but they do not reveal their causes. During the examination of the residuals, member states can be classified into three distinct categories: precisely predicted countries, notable overperformers, and notable underperformers.

4.4.1. Overperformers

Among the notable overperformers, Luxembourg shows a positive deviation of 10.97 percentage points (observed: 23.73%, predicted: 12.76%). This deviation may be hypothesized to relate to the country's distinctive concentration in knowledge-intensive international financial and holding services (Lahtinen et al., 2013). This aligns with Eurostat (2025a) data showing exceptionally high AI adoption in the information and communication sector (62.52%). Slovenia similarly displays a positive residual of 9.53 percentage points. Its position in highly automated automotive supply chains and smart factory integration (International Federation of Robotics, 2025; Statistical Office of the Republic of Slovenia, 2026) suggests that sector-specific technological intensity might foster AI use in ways not fully captured by a general national digital intensity indicator. Furthermore, Sweden, Denmark, and Belgium also display positive residuals, which may reflect the complementary organizational conditions generated by combining advanced digital competencies with technological depth to foster greater innovation capacity (Tangi et al., 2022).

4.4.2. Underperformers

Conversely, several member states display lower AI adoption than predicted by their structural digital endowments. Poland exhibits the largest negative residual (-7.89 percentage points). Despite a favorable DII value (70.01%), adoption may be constrained by institutional factors not modeled here. Surveys indicate that uncertainty regarding legal consequences (52.52%) and data privacy concerns (48.83%) act as prominent barriers across European enterprises (Eurostat, 2025a), which might be exacerbated in traditional manufacturing and agricultural segments, potentially further affected by geopolitical uncertainties (European Commission, 2023).

The patterns in underperforming countries with otherwise strong infrastructure, such as Romania (negative residual of 5.00 percentage points despite >82% broadband coverage) and Czechia (-5.32), resonate with the characteristics of the middle-income trap in digitalization (World Bank, 2024). These cases highlight that transitioning from basic connectivity to advanced algorithmic applications requires complex organizational transformations and R&D resources (European Commission, 2024c) that infrastructure alone cannot provide. Similarly, Italy's negative residual (-4.62) might be contextually related to the extensive fragmentation of its enterprise sector and the prevalence of traditional family-owned businesses (OECD, 2024), which face different investment capacities compared to technology-intensive industries. While these country-specific narratives provide plausible context, they remain speculative hypotheses. Because variables such as industrial structure, R&D expenditure, enterprise size distribution, and specific regulatory uncertainties were not included in the empirical model, they cannot be definitively identified as causes for the residuals. Nevertheless, these deviations strongly emphasize that AI adoption is shaped by a complex interplay of organizational and macro-level factors beyond infrastructure and basic digital skills, directing future research toward these omitted mechanisms.

4.5. Cluster Analysis

The regression model examined the conditional associations between the selected digital indicators and enterprise AI use. However, in order to get a comprehensive geopolitical map of Europe's digital fault lines, as a fourth analysis phase, a K-means cluster analysis was performed.

The analysis used three indicators representing broadband infrastructure, ICT specialist employment, and basic digital intensity. The three-cluster solution produced groups containing 8, 10, and 9 member states. The average silhouette coefficient was 0.341, the Calinski Harabasz index was 30.477, and the Davies Bouldin index was 0.923. Although the two-cluster solution showed stronger numerical validation, the three-cluster solution provided a more differentiated and substantively interpretable typology by distinguishing a transitional profile between the comparatively strong and weaker digital groups. The solution was retained because it provides a parsimonious representation of comparatively strong, intermediate, and weaker combinations of digital characteristics across EU member states. To address potential biases arising from unequal variable dispersion (e.g., the standard deviation of broadband is considerably larger than that of ICT specialists), a robustness check was performed by recalculating the K-means clustering using standardized Z-scores. The substantive country classification remained remarkably stable. The macro-structure of the three groups was preserved, with only four countries shifting their boundary positions (e.g., Ireland moving to the frontrunners cluster due to the increased weight of its strong ICT sector, and Portugal shifting to the transitional zone). This confirms that the unstandardized three-cluster solution provides a structurally robust and substantively reliable typology of European digital profiles. The results are illustrated in Figure 1.

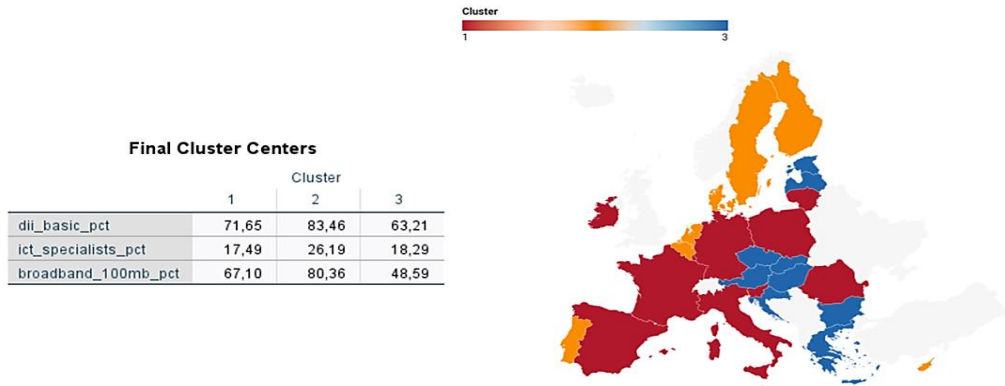


Figure 1. K-means Cluster Analysis of Digital Indicators in EU27

4.5.1. Digital Frontrunners

The cluster of digital frontrunners represents the group with the strongest combined profile across the three digital indicators examined in this study. Eight member states can be classified here: Belgium, Cyprus, Denmark, Finland, Malta, the Netherlands, Portugal, and Sweden.

The primary characteristic of this macro group is the exceptional maturity and balance of digital transformation along the examined variables. The cluster centroids point out that in this group, basic digitalization of the SME sector is a completed fact (DII cluster centroid: 83.46%). Human capital is the most highly trained in this macro-area: about a quarter of companies (ICT specialists mean: 26.19%) employ a dedicated IT specialist. All this is accompanied by excellent, over 80% (mean: 80.36%) 100 Mb/s broadband physical network penetration.

Geographically, the group is centered on the Scandinavian and Benelux states. The classification of Cyprus and Portugal is also notable because both countries combine comparatively strong broadband availability with relatively high DII values. Their comparatively strong digital profiles may provide favorable organizational conditions for integrating advanced AI applications. Based on their current digital characteristics, these countries appear comparatively well positioned to progress toward the EU targets for 2030.

4.5.2. Transitional Zone

The most populous group, comprising 10 member states, is the transitional zone, which includes France, Ireland, Poland, Lithuania, Luxembourg, Germany, Italy, Romania, Spain, and Slovenia.

This highly heterogeneous macro group represents the European average and asymmetrical development. Based on the cluster centroids, basic digitalization of companies is acceptable in this area, but not outstanding (DII mean: 71.65%), and their infrastructural coverage is average (broadband: 67.10%). Their weakest point is the scarce human resources: of the 3 groups, they have the lowest proportion of companies with specialized knowledge (ICT specialists cluster centroid is only 17.49%).

Their defining characteristic is asymmetry, which often embodies the middle-income trap. Although these countries perform comparatively well in some dimensions, (e.g., Spain or Romania have excellent optical infrastructure, and France and Germany are well-capitalized), their profiles remain uneven across the three indicators.

In these countries, AI adoption coexists with comparatively uneven levels of specialized expertise and organizational digitalization. Given their economic weight and heterogeneous digital profiles, their future development will be important for progress toward the EU's broader digital objectives.

4.5.3. Lagging Regions

The cluster analysis clearly shed light on the main digital divide of this group: the massive infrastructural lag. The cluster centroid of 100 Mb/s broadband connection is the lowest for them, only 48.59% (compared to values around 80% and 67% for the other two clusters). This is accompanied by the weakest general digital intensity (DII mean: 63.21%).

Interestingly, their human-capital position (ICT specialists: 18.29%) is marginally better than that of the transitional zone (17.49%); however, this human capital profile does not coincide with similarly strong infrastructural and organizational digital indicators.

This cluster includes countries such as Austria and Czechia, where comparatively lower broadband availability coexists with moderate levels of AI use. Historical and regulatory differences may offer possible explanations for these patterns, but they were not examined in the present model. For these countries, the findings suggest that policies addressing basic connectivity and SME digitalization could complement initiatives focused directly on AI adoption.

5. Discussion

The findings provide new insights into how the three-level digital divide framework can be applied to enterprise AI adoption across EU member states. The findings refine the three-level digital divide framework by suggesting that access, skills, and advanced technology use are complementary but not automatically sequential dimensions. The uneven combinations observed across countries indicate a configuration gap: strength in one dimension does not necessarily translate into widespread AI adoption when other organizational conditions remain underdeveloped.

The statistical results do not support a simple technologically deterministic interpretation in which physical access alone is closely associated with advanced technology adoption. Broadband showed no statistically significant bivariate relationship with AI adoption, and its conditional coefficient in the regression model was also not significant at the 5% level. The weak bivariate relationship and the negative but statistically uncertain broadband coefficient suggest that connectivity alone may not be closely associated with AI adoption and that its relevance may depend on complementary organizational capabilities.

Artificial intelligence can be understood as an advanced component of a broader corporate digital transformation process. General basic digital intensity has the strongest positive statistical association with AI adoption among the included variables ($B = 0.620$, $p < 0.001$). This relationship is theoretically plausible because DII captures broader digital practices, including the use of data, software, and connected business processes, that may provide an organizational environment supportive of advanced technology use. However, DII and AI adoption are also conceptually related manifestations of enterprise digital transformation. The observed association may therefore reflect complementary digital capabilities, reverse influence from AI adoption to digital intensity, or common factors affecting both indicators. The cross sectional design does not allow these possibilities to be distinguished or the direction of the relationship to be established.

The results are consistent with the broader argument that AI adoption is embedded in existing organizational digital practices. However, neither the negative intercept nor the cross-sectional coefficients establish a specific adoption threshold. The analysis also showed that the positive coefficient for ICT specialists

was not statistically significant after controlling for DII and broadband. This pattern may indicate that specialized expertise and general digital maturity are interrelated organizational characteristics, but the study does not test a mediating mechanism.

Finally, the K-means cluster analysis revealing macro-regional patterns also made the technological fragmentation of the European Union visible. The analysis distinguishes digital frontrunners, a heterogeneous transitional zone, and countries with comparatively weaker infrastructural and organizational digital profiles.

The Scandinavian and Benelux focused frontrunners combine comparatively strong expertise, infrastructure, and digital intensity, whereas the cluster with weaker digital profiles has average broadband availability of approximately 48% and lower basic digital intensity.

Taken together, the findings suggest that an exclusively infrastructure-focused approach may be insufficient to support progress toward the Digital Decade targets. The observed associations are consistent with considering a broader policy mix that complements connectivity investments with support for enterprise digital maturity, ICT capabilities, and a predictable regulatory environment.

6. Limitations

The findings must be interpreted in light of the small country-level sample. With 27 observations and three predictors, statistical power is limited, confidence intervals may be wide, and the estimates may be sensitive to individual countries. Although the leave-one-country-out analysis supports the stability of the main DII result, it does not eliminate the limitations of the cross-sectional design. Country-level aggregation may also conceal differences across industries, firm sizes, and individual enterprises.

The model may also be affected by omitted variable bias. However, due to the severely limited sample size inherently restricted to the 27 EU member states ($N=27$), introducing additional macro-level controls, such as GDP per capita, firm-size structure, detailed sectoral composition, R&D expenditure, or specific national AI policies, would critically deplete the model's degrees of freedom and compromise statistical reliability. Consequently, this study deliberately adopts a parsimonious specification. It must be strictly interpreted as an exploratory, associational analysis rather than a comprehensive explanatory causal model.

A further limitation concerns the conceptual proximity and potential endogeneity of DII and AI adoption. Both indicators capture aspects of enterprise digital transformation, creating a recognized conceptual and empirical overlap. The cross-sectional data cannot determine whether digital intensity precedes AI adoption, AI use contributes to higher digital intensity, or both are associated with omitted organizational conditions. Therefore, the DII coefficient should be viewed as a measure of interrelated digital maturity, a conditional association, rather than an independent causal trigger. The results must be strictly interpreted as exploratory cross-country associations.

As an exploratory technique, the cluster analysis provides an interpretable typology of EU digital profiles, although future studies could examine the stability of this classification using alternative cluster specifications and longitudinal data.

Future studies should use longitudinal or firm-level data to assess the temporal ordering and generalizability of these relationships.

7. Conclusion

This research provides an exploratory country-level assessment of how digital infrastructure, specialized human capital, and enterprise digital intensity are associated with AI adoption across the EU27.

The study's principal theoretical contribution is a configurational interpretation of the three-level digital divide: enterprise AI inequality reflects not only unequal access to infrastructure and skills, but also unequal organizational capacity to combine these resources and translate them into advanced technology use. The strong association between DII and AI adoption suggests that AI use is closely embedded in broader patterns of enterprise digitalization, although the direction of this relationship cannot be established from the present data. The results show that broadband availability is not significantly associated with AI adoption in the bivariate analysis and has a negative but statistically uncertain coefficient in the multivariate model. This pattern suggests that infrastructure alone may not be sufficient to account for differences in enterprise AI use, although the analysis does not establish a causal relationship.

The digital frontrunners, including Denmark, Finland, and Sweden, combine comparatively strong infrastructural, human capital, and organizational foundations with high levels of AI adoption, whereas the transitional and lagging clusters display more uneven digital profiles. These patterns are consistent with a persistent digital development gap, particularly among several Eastern and Southern European member states. In these countries, limited ICT expertise, identified as a major barrier by more than 70% of enterprises that

considered but did not adopt AI, together with legal, data protection, and ethical uncertainties, may constrain the organizational conditions associated with further digitalization.

From a practical perspective, these findings generate evidence-informed hypotheses for policy design. They suggest that infrastructure-oriented initiatives might benefit from complementary measures supporting enterprise digital maturity, workforce capabilities, and regulatory clarity. Rather than direct prescriptions derived from causal evidence, these results propose that EU funding could adopt a broader approach that also supports organizational preparedness for advanced technology use. Such programs could facilitate the development of internal data strategies, improvements in general digital intensity, and the continuous specialized training of the workforce. Given the cross-sectional design and the small macro-level sample, these practical implications remain exploratory priorities for further evaluation through longitudinal and firm-level research.

References

- AI-Enabled ICT Workforce Consortium. (2024). The transformational opportunity of AI on ICT jobs. Cisco. <https://www.cisco.com/c/dam/m/ai-enabled-ict-workforce-consortium/report.pdf>
- Akinwande, M. O., Dikko, H. G., & Samson, A. (2015). Variance inflation factor: As a condition for the inclusion of suppressor variable(s) in regression analysis. *Open Journal of Statistics*, 5(7), 754–767. <https://doi.org/10.4236/ojs.2015.57075>
- Andrews, D., Criscuolo, C., & Gal, P. N. (2016). The best versus the rest: The global productivity slowdown, divergence across firms and the role of public policy (OECD Productivity Working Papers No. 5). OECD Publishing. <https://doi.org/10.1787/63629cc9-en>
- Åström, J., Reim, W., & Parida, V. (2022). Value creation and value capture for AI business model innovation: A three-phase process framework. *Review of Managerial Science*, 16(7), 2111–2133. <https://doi.org/10.1007/s11846-022-00521-z>
- Babina, T., Fedyk, A., He, A. X., & Hodson, J. (2024). Artificial intelligence, firm growth, and product innovation. *Journal of Financial Economics*, 151, Article 103745. <https://doi.org/10.1016/j.jfineco.2023.103745>
- Calderón Gómez, D. (2021). The third digital divide and Bourdieu: Bidirectional conversion of economic, cultural, and social capital to (and from) digital capital among young people in Madrid. *New Media & Society*, 23(9), 2534–2553. <https://doi.org/10.1177/1461444820933252>
- Calvino, F., & Fontanelli, L. (2023). A portrait of AI adopters across countries: Firm characteristics, assets' complementarities and productivity (OECD Science, Technology and Industry Working Papers No. 2023/02). OECD Publishing. <https://doi.org/10.1787/0fb79bb9-en>
- Decision (EU) 2022/2481 of the European Parliament and of the Council of 14 December 2022 establishing the Digital Decade Policy Programme 2030 (Text with EEA relevance), 2022 O.J. (L 323) 4. <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32022D2481>
- Deursen, A. J. A. M., & Dijk, J. A. G. M. (2010). Measuring Internet skills. *International Journal of Human-Computer Interaction*, 26(10), 891–916. <https://doi.org/10.1080/10447318.2010.496338>
- Deursen, A. J. A. M., & Helsper, E. J. (2015). The third-level digital divide: Who benefits most from being online? In L. Robinson, S. R. Cotten, & J. Schulz (Eds.), *Communication and Information Technologies Annual (Studies in Media and Communications, Vol. 10, pp. 29–52)*. Emerald Group Publishing. <https://doi.org/10.1108/S2050-206020150000010002>
- Dijk, J. (2020). *The digital divide*. Polity Press.
- European Commission. (2023, September 27). Digital Decade Country Report 2023: Poland [Report]. https://piit.org.pl/wp-content/uploads/2023/09/DDR2023_Poland_country_report.pdf
- European Commission. (2024a). Second report on the State of the Digital Decade calls for strengthened collective action to propel the EU's digital transformation [Press release]. https://ec.europa.eu/commission/presscorner/api/files/document/print/en/ip_24_3602/IP_24_3602_EN.pdf
- European Commission. (2024b). Digital Decade Country Report 2024: Czechia [Report]. <https://ec.europa.eu/newsroom/dae/redirection/document/106708>
- European Commission. (2024c). Digital Decade Country Report 2024: Romania [Report]. <https://ec.europa.eu/newsroom/dae/redirection/document/106692>

- Eurostat. (2025a). Use of artificial intelligence in enterprises. Statistics Explained. Retrieved January 5, 2026, from <https://ec.europa.eu/eurostat/statistics-explained/SEPDF/cache/106920.pdf>
- Eurostat. (2025b). Towards Digital Decade targets for Europe. Statistics Explained. Retrieved January 5, 2026, from https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Towards_Digital_Decade_targets_for_Europe
- Eurostat. (2026). Artificial intelligence by size class of enterprise (isoc_eb_ai) [Data set]. Retrieved January 5, 2026, from https://doi.org/10.2908/ISOC_EB_AI
- Gallardo, R., Whitacre, B., & Grant, A. (2018). Broadband's impact: A brief literature review (Publication 001). Purdue Center for Regional Development. <https://pcrd.purdue.edu/wp-content/uploads/2018/12/Broadbands-Impact-Final.pdf>
- Gualandri, F., & Kuzior, A. (2024). Drivers of AI adoption in enterprises: A European-wide analysis. *Materials Research Proceedings*, 45, 240–248. <https://doi.org/10.21741/9781644903315-28>
- International Federation of Robotics. (2025, June 17). Europe's auto industry installed 23,000 new robots [Press release]. <https://ifr.org/ifr-press-releases/news/europes-auto-industry-installed-23000-new-robots>
- Ionașcu, C. M. (2025). Artificial intelligence adoption in the European Union: A data-driven cluster analysis (2021–2024). *Economies*, 13(5), Article 145. <https://doi.org/10.3390/economies13050145>
- Lahtinen, H., Halme, K., & Muller, E. (2013). Summary assessment of Luxembourg [Report]. European Commission. <https://ec.europa.eu/docsroom/documents/5125/attachments/1/translations/en/renditions/native>
- Laitsou, E., Gerogiannis, V. C., & Savvas, I. K. (2025). Artificial intelligence adoption in the European Union. ITS 33rd European Conference 2025: Digital Innovation and Transformation in Uncertain Times, Edinburgh, United Kingdom. International Telecommunications Society. <https://www.econstor.eu/bitstream/10419/331288/1/ITS-E-2025-43.pdf>
- OECD. (2023). OECD SME and Entrepreneurship Outlook 2023. OECD Publishing. <https://doi.org/10.1787/342b8564-en>
- OECD. (2024). OECD Economic Surveys: Italy 2024. <https://doi.org/10.1787/78add673-en>
- OECD. (2025). Closing broadband connectivity divides for all [Report]. https://www.oecd.org/en/publications/closing-broadband-connectivity-divides-for-all_d5ea99b2-en.html
- Ragnedda, M. (2017). The third digital divide: A Weberian approach to digital inequalities. Routledge. <https://doi.org/10.4324/9781315606002>
- Riggins, F. J., & Dewan, S. (2005). The digital divide: Current and future research directions. *Journal of the Association for Information Systems*, 6(12), 298–337. <https://doi.org/10.17705/1jais.00074>
- Statistical Office of the Republic of Slovenia. (2026). Research and development activity, detailed data, 2024 [News release]. <https://www.stat.si/StatWeb/en/News/Index/14165>
- Tangi, L., Van Noordt, C., Combetto, M., Gattwinkel, D., & Pignatelli, F. (2022). AI Watch. European landscape on the use of Artificial Intelligence by the Public Sector. Publications Office of the European Union. <https://doi.org/10.2760/39336>
- World Bank. (2024). World Development Report 2024: The middle-income trap. World Bank. <https://www.worldbank.org/en/publication/wdr2024>

Appendix A: K-means Cluster Validation Statistics

The table below presents the numerical validation indices for the alternative cluster configurations (k=2 to 6) evaluated during the exploratory analysis. While k=2 exhibits the strongest Silhouette and Calinski-Harabasz scores, the k=3 solution was selected for the final analysis to capture a substantively meaningful "transitional zone" that more accurately reflects the fragmented digital development stages across the EU.

<i>Number of Clusters (k)</i>	<i>Silhouette Score</i>	<i>Calinski-Harabasz Index</i>	<i>Davies-Bouldin Index</i>
2	0.472	39.96	0.753
3	0.369	32.79	0.892
4	0.349	31.70	0.925
5	0.335	30.47	0.874
6	0.326	27.36	0.863

Note: Metrics in this table reflect an exploratory multi-k grid evaluation (Python KMeans), while the final 3-cluster partition reported in Section 4.5 derives from the SPSS Quick Cluster procedure (yielding Silhouette = 0.341, CH = 30.48, DB = 0.923).