AI Adoption in EU Enterprises: a Comprehensive Analysis and Modelling of Usage Patterns, Sectoral Differences and Acquisition Trends

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Abstract

This paper analyses recent data on AI technology use among EU enterprises, highlighting AI's rapid advancement and its benefits in transport safety, manufacturing efficiency, sustainable energy, and decision-making. AI technologies – such as text mining, computer vision, speech recognition, natural language generation, machine learning, and deep learning – enable data-driven predictions, recommendations, and decisions with varying autonomy. AI systems can be software-based (e.g., virtual assistants) or device-embedded (e.g., autonomous robots, drones). Our findings reveal a significant increase in AI adoption rates between 2021 and 2023, driven by improvements in digital infrastructure, regulatory support, and sectoral advancements. However, barriers such as limited resources, skill shortages, and data security remain significant for SMEs. The study examines current AI adoption trends across EU countries and models key factors influencing AI adoption from 2021 to 2023 using panel data analysis.

Keywords	***DOI***	***JEL code***
AI technologies, EU enterprises, panel modelling, statistical analysis, AI adoption	*https://doi.org/10.54694/stat.2024.75*	*C55, O33, L86, C55*

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INTRODUCTION

The adoption of artificial intelligence (AI) technologies among enterprises in the European Union (EU) has accelerated in recent years, driven by broader trends in digital transformation and innovation. However, AI adoption remains highly uneven across firms and sectors, influenced by varying levels of economic development, digital infrastructure, and regulatory environments. A deeper understanding of these factors is essential to support evidence-based policymaking and strategic decision-making within businesses.

This paper aims to analyze AI adoption trends among EU enterprises between 2021 and 2023, focusing on sectoral differences and key economic and regulatory drivers. By examining the interplay between economic indicators, digital infrastructure, and policy support, this study provides insights into the factors facilitating or hindering AI diffusion. Particular attention is given to small and medium-sized enterprises (SMEs), which face unique challenges related to limited financial and technical resources. Addressing these challenges is crucial for bridging the digital divide and fostering inclusive AI-driven growth across EU economies.

The European Commission's *Shaping Europe's Digital Future* strategy, along with the *European Strategy for Data* and the *White Paper on Artificial Intelligence*, has emphasized the importance of AI regulation and data-driven decision-making. The *Digital Compass for the EU's Digital Decade* has further set ambitious targets for AI adoption, skills development, and digital infrastructure expansion by 2030 (Mikalef et al., 2021). However, progress in AI adoption varies significantly by enterprise size and sector. While large firms (28%) and technology-intensive industries are leading in AI integration, manual and resource-constrained sectors continue to face barriers such as high costs, skill shortages, and data security concerns (Azzutti, 2022; Brodny and Tutak, 2022; Benbya et al., 2020; Mihai et al., 2023).

AI acquisition methods also differ by firm size. Large enterprises primarily develop AI in-house, acquire AI-driven companies, or form strategic partnerships, whereas SMEs rely heavily on commercial AI solutions due to resource limitations (European Commission, 2024; Marino et al., 2023). Security and privacy concerns further impact adoption, particularly in high-risk industries like energy, where AI-related safety risks require careful regulatory oversight (Fontes et al., 2023; Heymann et al., 2023). Despite these challenges, the increasing recognition of AI's benefits across all business sizes suggests that adoption rates will continue to rise, albeit unevenly.

This study defines AI technologies as systems capable of autonomous decision-making and predictive modeling, distinguishing them from traditional data analytics tools. By employing panel data analysis, principal component analysis (PCA), and cluster analysis, we aim to provide a structured, data-driven assessment of AI adoption trends and their underlying determinants. The findings contribute to the ongoing discourse on AI policy, digital infrastructure development, and business strategies for AI integration within the EU.

1 LITERATURE REVIEW

Building on foundational studies of AI adoption, this section examines the factors driving and inhibiting AI integration across various enterprise sizes and sectors within the EU. By reviewing key advancements, sectoral differences, and regulatory influences, we establish a contextual framework for analyzing AI usage trends, sectoral adoption patterns, and acquisition methods.

1.1 AI adoption in companies

Larger companies, such as Google and Amazon, lead in ambitious AI projects – autonomous vehicles, drone delivery, cashier-free retail – thanks to their significant resources and partnerships, which enable cutting-edge AI implementations (Benbya et al., 2020). Firms with robust finances and technical capabilities leverage AI to modernize operations, reduce costs, and boost efficiency (Agarwal, 2023). By 2020, AI had already influenced sectors like finance and life sciences worldwide (Benbya et al., 2020).

SMEs are essential to the EU's digital transformation, but adoption varies, with Scandinavian countries leading and Eastern Europe lagging (Brodny and Tutak, 2022). Challenges for SMEs include limited resources, complicating AI adoption efforts (Marino et al., 2023). Without strategic planning, rushed AI integration can strain SMEs, though manufacturing SMEs are beginning to realize AI's benefits (Gladysz et al., 2023). Open innovation platforms facilitate SME-AI developer collaborations, offering accessible, low-bureaucracy interfaces (Gladysz et al., 2023).

SMEs, comprising 99% of EU firms, employ nearly 100 million people and contribute over half of Europe's GDP, underscoring their societal importance (Brodny and Tutak, 2022). Digital maturity does not correlate directly with GDP; leading nations like Denmark invest in digital skills, while others, such as Romania, Bulgaria, and Greece, lag (Brodny and Tutak, 2022).

1.2 Sectorial differences

AI holds transformative potential across various sectors, though its use in 2020 was largely experimental. Companies employ AI to boost efficiency, cut costs, improve products, and enhance decision-making (Benbya et al., 2020). In business administration, AI optimizes workflows and reduces expenses (Mihai et al., 2023), while in marketing and sales, it automates tasks, with conversational AI benefiting finance, retail, and healthcare (Benbya et al., 2020). AI could revolutionize sectors like building management, HVAC, transportation, and power grids by enhancing decision-making and integrating energy demands without major infrastructure upgrades (Farghali et al., 2023). In the energy sector, AI improves forecasting and bidding, boosting reliability and affordability (Niet et al., 2023).

Manufacturing has utilized robotic AI for repetitive tasks, now progressing to collaborative robots ("cobots") for more complex roles, though adoption is limited by skill shortages and often depends on external providers (Benbya et al., 2020; Maddikunta et al., 2022; Gladysz et al., 2023). IoT is anticipated to be critical to manufacturing's future (Gladysz et al., 2023).

In HR, AI reshapes tasks like resume screening and candidate classification, widely used in IT and e-commerce to improve recruitment processes and fairness (Mihai et al., 2023; Pillai et al., 2024). Effective AI integration requires technical expertise, benefiting organizations broadly (Agarwai, 2023).

1.3 Approaches for integration

Introducing new technology in the workplace brings both opportunities and challenges, requiring organizations to plan their responses carefully (Pachidi et al., 2021). Companies should create action plans for AI and ML implementation, especially in a VUCA (volatile, uncertain, complex, ambiguous) environment, to address concerns about job loss and discrimination, which can be mitigated through collaboration (Kumar et al., 2023).

Effective AI use relies on data quality and skilled talent, with open data environments supporting innovation, though data security remains essential (Marino et al., 2023; Gladysz et al., 2023). HR should evaluate tasks that benefit from automation to improve efficiency and add value locally or broadly (Agarwai, 2023). Balancing automation with augmentation aids sustainability by allowing employees to focus on creative skills (Kumar et al., 2023). Additionally, managers need to clarify AI-related responsibilities and legal liabilities (Benbya et al., 2020).

Employee resistance to AI varies, sometimes leading to symbolic compliance that may prompt broader organizational changes, even department eliminations (Pachidi et al., 2021). Transparent algorithms are essential, as non-transparent evaluations may feel controlling (Rahman, 2021). Maintaining open communication enhances employee experience (EEX) from recruitment onward (Pillai et al., 2024), and involving employees in AI feedback can alleviate job security concerns and foster trust (Kumar et al., 2023).

1.4 AI governance

The European Commission's AI vision, initiated in 2018, highlighted digital disparities among EU states (Fontes et al., 2023; Mihai et al., 2023). Leading in AI adoption are Denmark, Finland, Belgium, Sweden, and Lithuania, with Ireland, Malta, and Denmark at the forefront of digital advancement (Marino et al., 2023). Robotic process automation and machine learning are common, though automated robots remain limited (Mihai et al., 2023), as establishing AI standards is a lengthy process (Benbya et al., 2020).

Growing demand for ethical AI has spurred organizations to create guidelines focused on ethical frameworks to mitigate risks (Birkstedt et al., 2023; Mainzer, 2019). EU policies support human-centric AI and ban high-risk applications (Heymann et al., 2023). Collaboration across companies, academia, and institutions, particularly in low-tech sectors, is essential for innovation, aided by government support like tax incentives and GDPR-aligned data practices (Benbya et al., 2020; Marino et al., 2023).

AI governance sets rules to align technology with organizational values and legal standards (Birkstedt et al., 2023), supporting improved decision-making (Cui et al., 2022). The EU aims for 90% of SMEs to achieve a basic digital level by 2030, fostering a startup-friendly environment (Mihai et al., 2023; Marino et al., 2023). Gaps in governance highlight the need for AI oversight units and ethics training, as AI's complexity demands skilled experts across fields (Azzutti, 2022; Birkstedt et al., 2023).

1.5 Opportunities and risks

The global AI race, especially in Europe, is shaped by policies balancing competitiveness with ethics (Girasa, 2020). AI's broad applications encourage adoption for agility, resource transformation, and opportunity capture (Fontes et al., 2023; Kumar et al., 2023). An innovation-driven culture may help companies fully leverage AI, potentially requiring strategic shifts to keep up with rapid technological change (Marino et al., 2023).

Machine learning (ML) is becoming essential in decision-making, reducing bias and inefficiency through data-driven insights (van der Broek et al., 2021). The Internet of Things (IoT) also supports productivity through real-time data analysis, though some technologies will still need human input (Mihai et al., 2023). Future AI priorities focus on governance, democratized data science, transparency, and ethical oversight for responsible AI use (Benbya et al., 2020; Fontes et al., 2023).

AI's speed and analytical power heighten risks of market crises and manipulation, prompting the EU to limit high-risk applications (Azzutti, 2022; Heymann et al., 2023). Ethical concerns, including privacy and autonomy, can be challenged in crisis contexts (Fontes et al., 2023; Niet et al., 2023). Despite leading AI development, private industry faces regulatory, talent, and data challenges (Marino et al., 2023). AI's role in automating tasks is reshaping workplaces and creating demand for professionals with combined business and technical skills (Benbya et al., 2020). However, AI-driven control over employee evaluations can spur resistance, or "algoactivism" (Kellogg et al., 2020), and chatbots may pose privacy and language concerns (Pillai et al., 2024).

AI data can be biased, necessitating regular reviews to prevent flawed outcomes (Kellogg et al., 2020). Complex systems may act unpredictably, raising issues of privacy, control, and transparency (Benbya et al., 2020; Azzutti, 2022). AI adoption also influences labor and economic metrics, shifting roles toward data management (Kellogg et al., 2020). Positive attitudes, good data practices, and skill alignment are critical to achieving economic benefits, reflecting AI's role in European policy and labor dynamics (Somjai et al., 2020).

1.6 Research contribution

This paper enhances understanding of AI adoption in the EU by analyzing recent data on AI usage across sectors and enterprise sizes, identifying leading and lagging sectors, and highlighting areas for growth and investment. It examines AI acquisition methods – whether through internal development, external purchases, or partnerships – offering insights into integration strategies.

Through panel data analysis from 2021 to 2023, the study models economic, infrastructural, and policy factors influencing AI adoption. Findings inform policymakers on supporting AI adoption in underperforming sectors and regions, emphasizing the importance of digital infrastructure for AI integration and economic growth.

This study identifies gaps for further research, such as longitudinal and comparative studies, to track trends and effective adoption strategies. Visualizations of AI adoption by country, enterprise size, and sector make complex data accessible. Overall, the paper provides academic insights and practical policy recommendations on AI adoption trends in the EU.

The structure is as follows: Section 2 covers data and methodology, Section 3 presents empirical results, Section 4 presents limitations and future research directions, and last section concludes.

2 DATA AND METHODOLOGY

2.1. Data

The data were collected for the EU countries from the Eurostat database. The dataset comprises the following variables:

- AI Technology Adoption: The percentage of enterprises using at least one AI technology in 2021 and 2023.
- Economic Indicators: GDP at market prices (in million EUR) and the real GDP growth rate (in percentage).
- Broadband Connection Usage: The distribution of maximum internet speeds available, ranging from less than 30 Mb/s to at least 1 Gb/s.
- Internet Usage Patterns: Usage percentages for desktop computers, laptops, tablets, smartphones, and other mobile devices.
- Expenditure and Inflation: The volume indices of real expenditure per capita (in Purchasing Power Standards, PPS) and the Harmonised Index of Consumer Prices (HICP).

The dataset includes 27 entries, one for each EU country, with no missing values for any of the 18 columns, collected for 2021 and 2023.[6]

2.2 Methodology

Our approach involves the use of data analysis to model the key factors influencing AI adoption from 2021 to 2023 by employing a combination of descriptive statistics, principal component analysis (PCA), and panel data modeling. PCA was used to address multicollinearity among variables and to reduce dimensionality, transforming the dataset into principal components that capture the maximum variance. The Hausman test was employed to determine the suitability of fixed or random effects models, ensuring robust and unbiased estimates.

Cluster analysis was also conducted to group countries with similar AI adoption patterns, providing insights into shared drivers and barriers across clusters.

2.2.1 Dimensionality reduction and regression modelling

To address multicollinearity and reduce the dimensionality of our dataset, we apply Principal Component Analysis (PCA). PCA transforms the original variables into a new set of uncorrelated variables called principal components, which capture the maximum variance in the data. Then, we use these components in the following regression model:

[6] Data and code are available via Quantlet: <*https://github.com/QuantLet/AIAdoptionEU*>.

$$\text{AI\_Adoption}_{it} = \gamma_0 + \gamma_1 PC_{k1_{it}} + \gamma_2 PC_{2_{it}} + \ldots + \gamma_k PC_{k_{it}} + \epsilon_{it}. \tag{1}$$

By employing this methodology, we aim to provide a robust analysis of the factors influencing AI adoption in EU enterprises, accounting for both within-country and between-country variations.

2.2.2 Panel data modelling

We employ a fixed effects panel data model to account for both the temporal and cross-sectional dimensions of the data. The general form of the fixed effects model is given by:

$$Y_{it} = \alpha_i + \beta X_{it} + \epsilon_{it}, \tag{2}$$

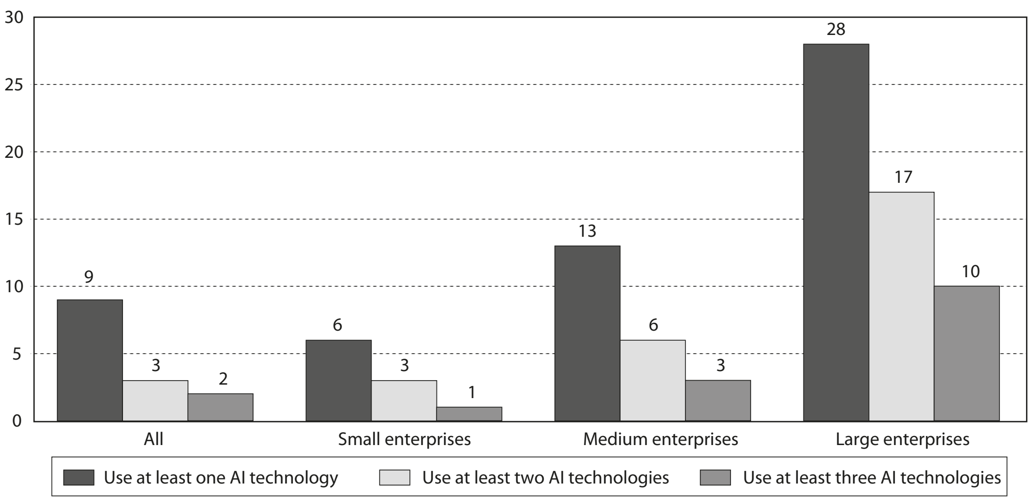
where:

- Y_{it} is the dependent variable representing the AI adoption rate for country i at time t,
- α_i represents the country-specific fixed effect,
- X_{it} is a vector of independent variables, i.e. the principal components extracted at previous step,
- β is a vector of coefficients to be estimated,
- ϵ_{it} is the error term.

3 EMPIRICAL RESULTS

In 2021, 8% of EU enterprises with 10+ employees adopted at least one AI technology, including text mining, speech and image recognition, natural language generation, machine learning, process automation, or autonomous movement. Only 3% adopted two AI technologies, and 2% used three or more (Figure 1). Adoption rates varied by company size: 6% of small, 13% of medium, and 28% of large enterprises used AI, reflecting economies of scale and affordability advantages for larger firms.

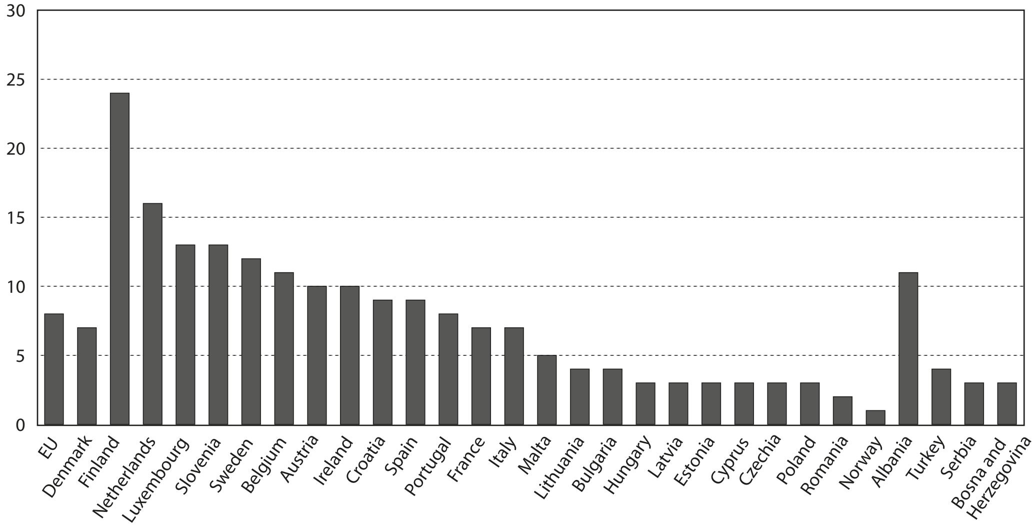
Figure 1 Enterprises using AI technologies, by size class, EU, 2021 (% of enterprises)



Source: Eurostat (isoc_eb_ai)

Across EU countries, AI adoption in 2021 ranged from 1% in Romania to 24% in Denmark, with Finland (16%) and the Netherlands and Luxembourg (13%), see Figure 2.

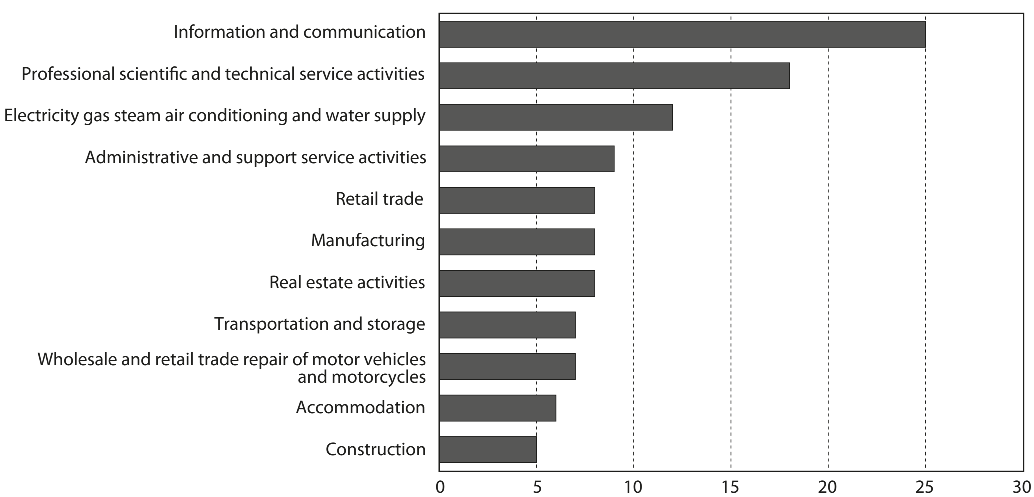
Figure 2 Enterprises using AI technologies by country, 2021 (% of enterprises)



Source: Eurostat (isoc_eb_ai)

Sectoral differences were notable, with the information and communication sector (25%) and professional services (17%) showing the highest AI use. Other sectors remained below 10% (Figure 3).

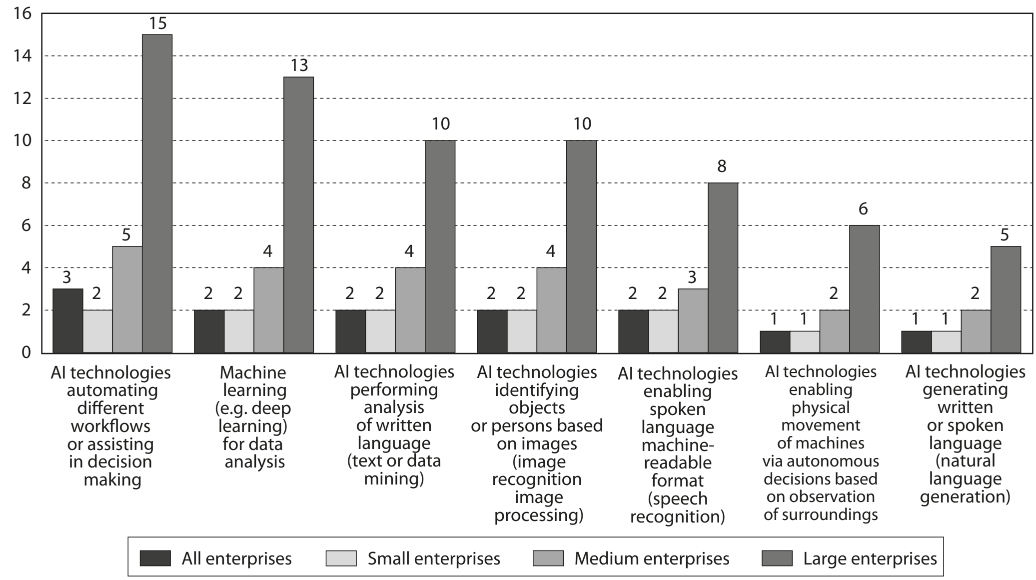
Figure 3 Enterprises using AI technologies, by economic activity, EU, 2021 (% of enterprises)



Source: Eurostat (isoc_eb_ai)

EU enterprises adopted diverse AI technologies, with robotic process automation (3%) being the most common, followed by image recognition, machine learning, text mining, and speech recognition (each 2%), and autonomous machine movement and natural language generation (1%) (Figure 4). Large enterprises favored workflow automation (15%) and machine learning (13%), while natural language generation saw the lowest adoption at 5%.

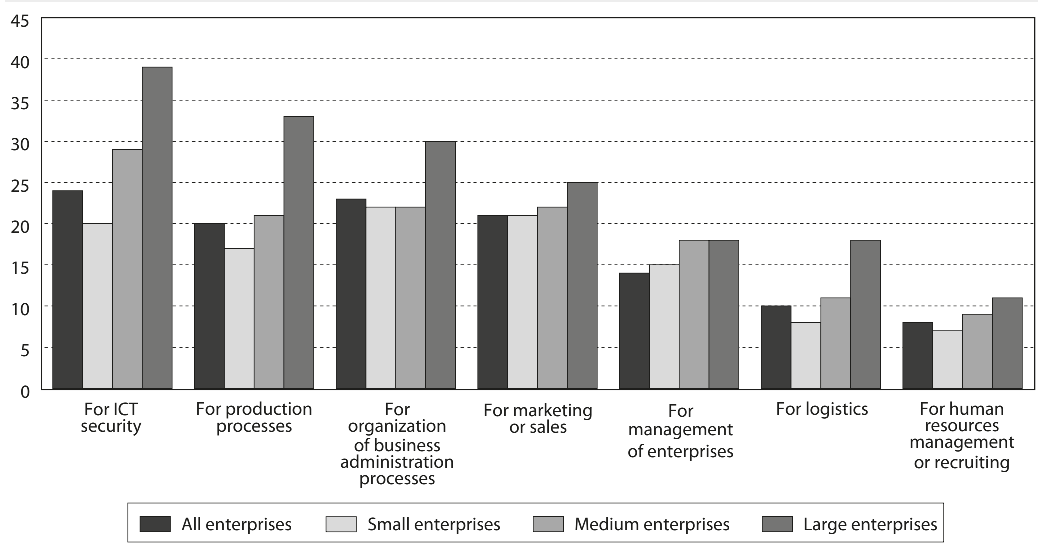
Figure 4 Enterprises using AI technologies by type of AI technology and size class, EU, 2021 (% of enterprises)



Source: Eurostat (isoc_eb_ai)

In 2021, AI use by EU enterprises spanned multiple functions, with ICT security (24%) and business administration (23%) being the most common. HR-related AI was the least used (8%). Large enterprises were more likely to use AI for ICT security (39% vs. 20% in small enterprises), production processes (33% vs. 17%), and logistics (18% vs. 8%) (Figure 5).

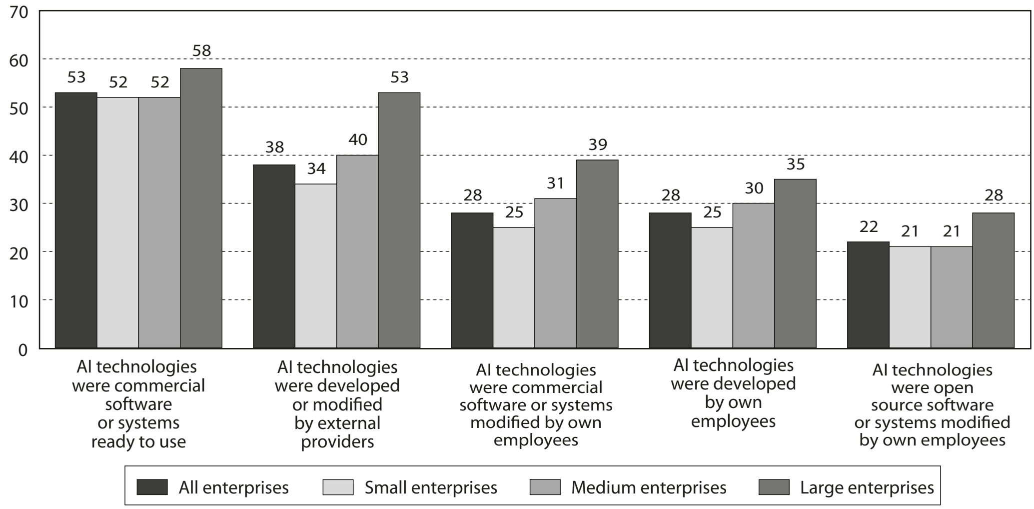
Figure 5 Enterprises using AI software and systems by type of purpose and size class, EU, 2021 (% of enterprises using at least one AI technology)



Source: Eurostat (isoc_eb_ai)

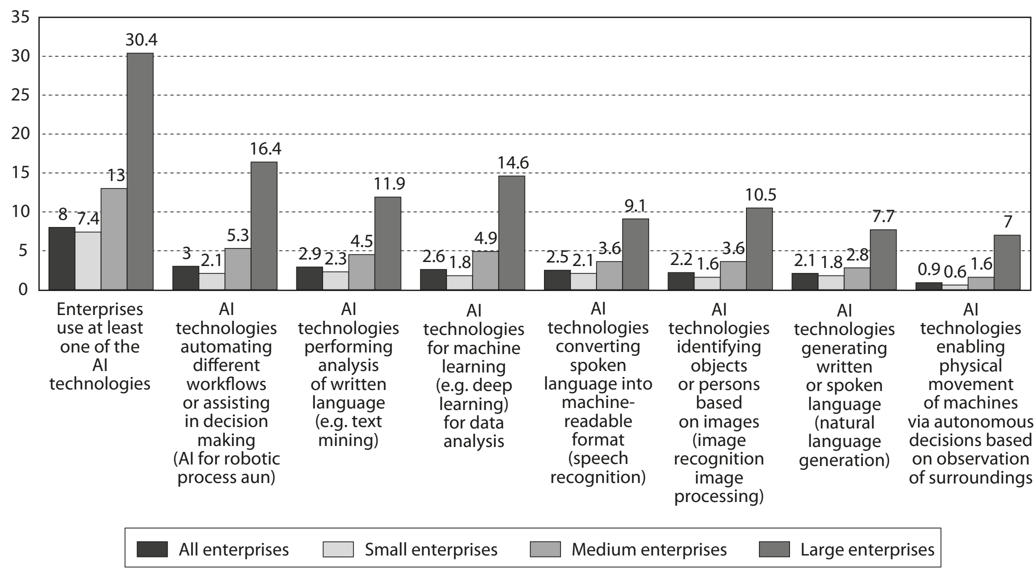
Most enterprises acquired AI through commercial software (53%), while 38% used AI from external providers, and 28% developed AI internally or modified commercial AI software. Open-source AI software modification was also common among 22% of enterprises (Figure 6). Acquisition methods varied by enterprise size, with larger firms more likely to rely on external providers (53%) and modify commercial software internally (39%).

Figure 6 Enterprises using AI technologies by source of acquisition and size class, EU, 2021 (% of enterprises using at least one AI technology)



Source: Eurostat (isoc_eb_ai)

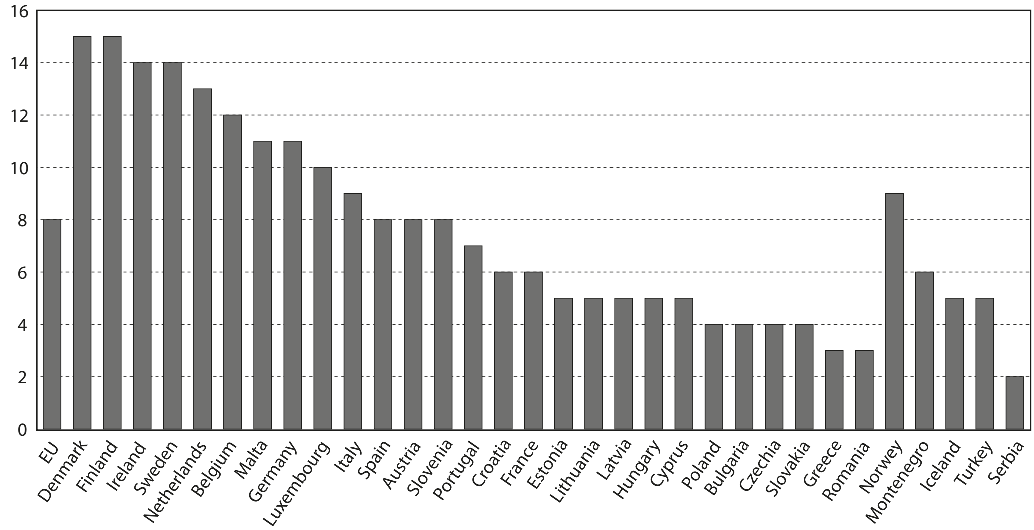
Figure 7 Enterprises using AI technologies by source of acquisition and size class, EU, 2023 (% of enterprises using at least one AI technology)



Source: Eurostat (isoc_eb_ai)

This analysis shows diverse AI adoption patterns across EU countries, reflecting varying economic performance, technology infrastructure, and digital engagement, with significant growth in AI use between 2021 and 2023 (Figure 8).

Figure 8 Enterprises using AI technologies, EU, 2023 (% of enterprises)



Source: Eurostat

In 2021, 8% of enterprises adopted at least one AI technology, with larger enterprises significantly outpacing SMEs. By 2023, AI adoption grew to 12%, marking a substantial increase, particularly among SMEs. This growth reflects improved digital infrastructure, such as high-speed broadband availability, and targeted regulatory incentives in lagging regions.

3.1 Cluster analysis

Descriptive and literature analysis shows significant variation in AI adoption across countries, sectors, and enterprise sizes. Cluster analysis groups countries with similar AI adoption patterns, helping policymakers design targeted initiatives to support lagging sectors or regions (Table 1).

Table 1 Clusters of EU countries by AI adoption

Cluster	2021 countries	2023 countries
Cluster 0 (low adoption)	Bulgaria, Cyprus, Czechia, Estonia, France, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden	Bulgaria, Cyprus, Czechia, Estonia, France, Greece, Hungary, Italy, Latvia, Lithuania, Malta, Poland, Romania, Slovenia, Spain
Cluster 1 (moderate adoption)	Austria, Belgium, Croatia, Finland, Germany, Spain	Austria, Croatia, Ireland, Portugal, Slovakia
Cluster 2 (high adoption)	Denmark	Belgium, Denmark, Finland, Germany, Luxembourg, Netherlands, Sweden

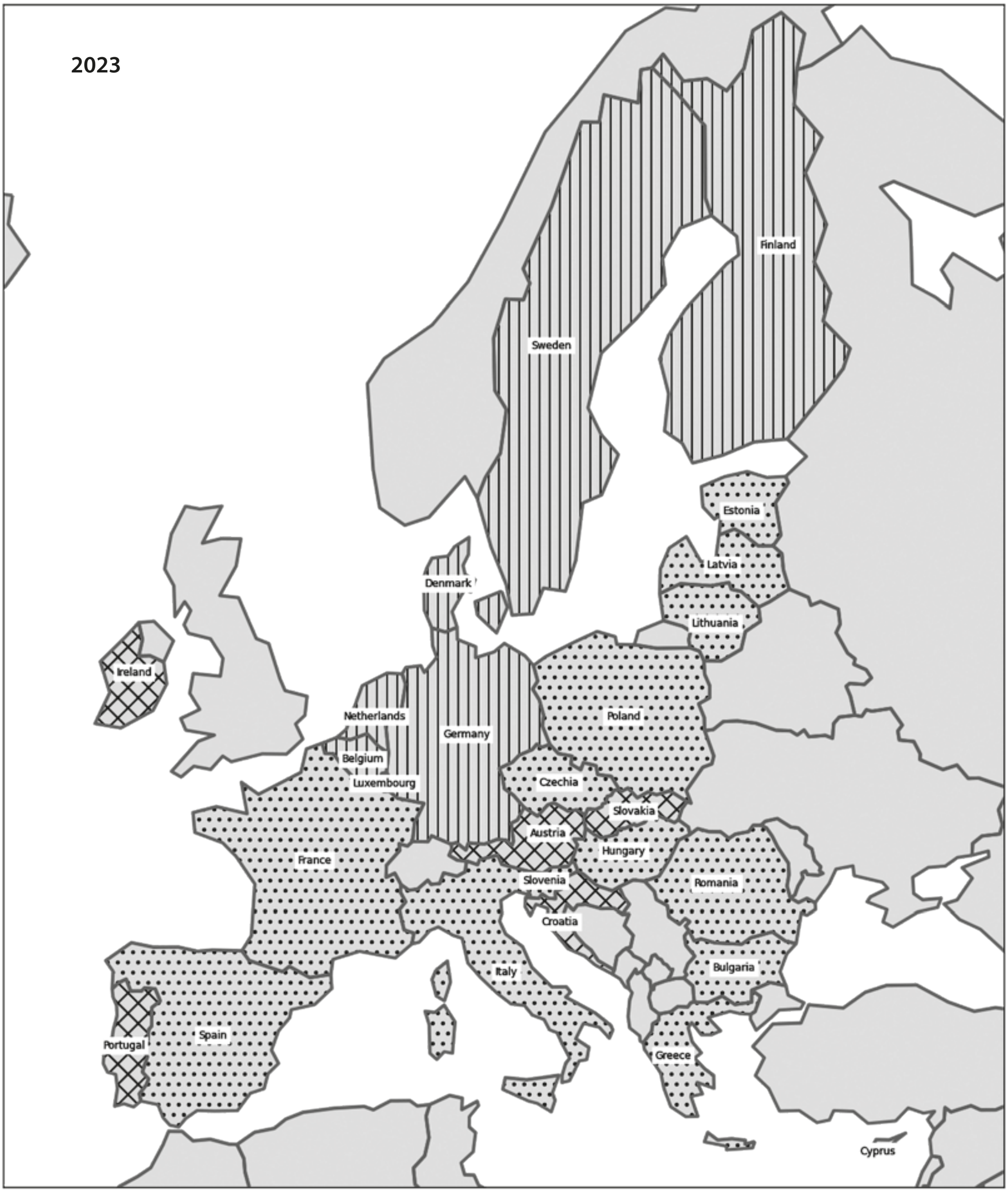
Source: Authors' calculations

Tracking cluster changes from 2021 to 2023 reveals that low-adoption countries (Cluster 0) remained stable, while moderate and high-adoption clusters showed country movement, indicating progress due to strategic investments and policies. Cluster 2 grew from one country in 2021 to five in 2023, reflecting increased AI adoption and policy influence. Countries like Austria, Belgium, Croatia, Finland, and Germany advanced to higher clusters, showing improvements in AI utilization (Figure 9).

Figure 9 Clusters of European countries by AI adoption level: low (dots), medium (lines), high (crosshatch)

Source: Authors' calculations

Figure 9 (continuation)



Source: Authors' calculations

3.2 Dimensionality reduction and regression modelling

Further, we used PCA for dimensionality reduction, aiming to mitigate multicollinearity and focus on components that capture the most variance.

For each year, 5 principal components were selected, accounting for more than 80% of total variance (81.29% for 2021 and 81.55% for 2023). Figure 10 displays the loadings of these principal components, for each year.

Figure 10 PCA loadings

PCA Loadings for 2021 – first 5 principal components

Variable	PC1	PC2	PC3	PC4	PC5
GDP at market prices mil EUR	0.040	–0.011	0.500	–0.536	0.404
Real GDP growth rate – volume %	–0.056	0.443	–0.032	0.536	0.304
Enterprises use DSL or other fixed broadband connection %	0.205	0.172	0.504	0.002	–0.368
MAX speed is less than 30 Mb/s %	–0.291	0.378	0.012	–0.099	0.003
MAX speed is at least 100 Mb/s but less than 500 Mb/s %	0.292	–0.237	0.091	0.224	–0.355
Max speed is at least 500 Mb/s but less than 1 Gb/s %	0.257	–0.157	0.256	0.126	0.372
Max speed is at least 1 Gb/s %	0.254	–0.219	0.305	0.152	–0.034
Individuals used the internet on a desktop computer %	–0.088	0.393	0.044	–0.380	–0.314
Individuals used the internet on a laptop %	0.314	0.045	–0.274	–0.197	–0.117
Individuals used the internet on a tablet %	0.349	0.243	–0.002	–0.137	0.013
Individuals used the internet on a smartphone %	0.361	0.045	–0.141	0.076	0.063
Individuals used the internet on a mobile device %	0.357	0.119	–0.194	–0.110	0.092
Individuals used the internet on other mobile device %	0.304	0.158	–0.245	–0.112	–0.182
Volume indices of real expenditure per capita (in PPS_EU27_2020=100)	0.263	0.238	–0.122	–0.056	0.409
HICP – annual data (average index and rate of change)	–0.075	–0.435	–0.345	–0.302	0.133

PCA Loadings for 2023 – first 5 principal components

Variable	PC 1	PC 2	PC 3	PC 4	PC 5
GDP at market prices mil EUR	0.060	0.083	0.582	0.317	0.344
Real GDP growth rate – volume %	–0.051	0.462	0.054	–0.421	–0.318
Enterprises use DSL or other fixed broadband connection %	0.168	0.340	0.221	–0.192	0.293
MAX speed is less than 30 Mb/s %	–0.297	–0.167	0.382	–0.190	–0.110
MAX speed is at least 100 Mb/s but less than 500 Mb/s %	0.197	0.123	–0.436	–0.180	0.622
Max speed is at least 500 Mb/s but less than 1 Gb/s %	0.249	0.361	–0.021	0.295	–0.293
Max speed is at least 1 Gb/s %	0.280	0.291	–0.014	0.036	–0.328
Individuals used the internet on a desktop computer %	0.161	–0.429	0.193	–0.294	–0.060
Individuals used the internet on a laptop %	0.273	–0.295	0.080	–0.058	–0.233
Individuals used the internet on a tablet %	0.361	–0.084	0.246	–0.082	0.046
Individuals used the internet on a smartphone %	0.367	–0.065	–0.160	0.005	–0.137
Individuals used the internet on a mobile device %	0.374	–0.135	–0.069	0.065	–0.058
Individuals used the internet on other mobile device %	0.295	–0.181	–0.037	–0.398	0.044
Volume indices of real expenditure per capita (in PPS_EU27_2020 = 100)	0.260	–0.098	0.089	0.459	0.059
HICP – annual data (average index and rate of change)	–0.197	–0.251	–0.358	0.242	–0.123

Source: Authors' calculations

The PCA loadings for 2021 and 2023 show shifts in how economic growth, broadband speeds, and internet usage are connected. In 2021, PC1 links economic growth and high-speed broadband (positive loadings on GDP growth and fixed broadband) with reduced mobile internet usage, suggesting a stronger association between economic growth and high-speed broadband over mobile connectivity. By 2023, PC1 shifts, with mobile internet usage becoming a positive indicator, along with GDP growth and broadband speeds, indicating a growing economic reliance on mobile connectivity.

In 2021, PC2 emphasizes economic growth and enterprise broadband over desktop internet, while by 2023, it focuses more on mid-range broadband speeds, showing a shift away from desktop reliance. By 2023, PC3 links mid-range broadband speeds and consumer spending, with mobile usage as a negative factor, suggesting moderate internet speeds support stable consumer spending with less mobile dependency.

Overall, the principal components highlight an increasing importance of mobile and high-speed broadband as economic indicators, with decreasing emphasis on traditional GDP and desktop internet by 2023. This shift underscores the role of digital and mobile connectivity in fostering economic growth and technological advancement.The results of the regression model, for 2021 and 2023, are shown in Table 2.

Table 2 Clusters of EU countries by AI adoption

	2021 ($R^2 = 0.593$)				2023 ($R^2 = 0.537$)			
	Coefficient	std. error	t-value	p-value	Coefficient	std. error	t-value	p-value
Constant	7.711	0.606	12.733	0.000	8.219	0.532	15.454	0.000
PC1	–1.334	0.296	–4.513	0.000	–1.185	0.178	–6.664	0.000
PC2	0.662	0.356	1.861	0.063	–0.029	0.299	–0.097	0.923
PC3	0.877	0.450	1.951	0.051	–0.408	0.472	–0.864	0.387
PC4	0.342	0.562	0.608	0.543	–0.153	0.602	–0.255	0.799
PC5	–0.951	0.553	–1.721	0.085	–0.318	0.555	–0.573	0.567

Source: Authors' calculations

The regression analysis reveals shifting factors in AI adoption from 2021 to 2023. A consistent finding is the inverse relationship with PC1: as mobile internet usage increases relative to traditional economic indicators, AI adoption decreases, likely due to infrastructure or compatibility issues.

PC2 and PC3, initially marginally significant in 2021, lost relevance by 2023. Economic growth, broadband usage, and consumer spending appear less central to AI decisions, suggesting a shift as organizations prioritize other technological and operational factors.

PC4 and PC5 remained insignificant, indicating that certain high-speed broadband and desktop internet usage metrics do not strongly influence AI adoption. This suggests that while digital infrastructure is important, not all connectivity aspects equally impact AI adoption.

Overall, the analysis highlights a move away from traditional economic factors in AI adoption, reflecting a more nuanced interaction between infrastructure, connectivity, and evolving business needs.

3.3 Panel models

To differentiate between variation over time within the same country and variation between different countries to develop a more accurate analysis by controlling for unobserved heterogeneity – individual characteristics that may not change over time and are not captured by the observed variables but could affect the outcome variable, we have performed panel modelling.

This study examines factors influencing AI adoption using fixed-effects and random-effects models on panel data from 2021 and 2023, with principal components (PCs) derived from economic and technological indicators as explanatory variables, and AI adoption as the dependent variable. The Hausman test helps select the preferred model between fixed and random effects.

Table 3 Panel regression models

	Fixed effects	Random effects
Dep. variable	AI_adoption	AI_adoption
Estimator	Panel OLS	Random effects
No. observations	54	54
Cov. est.	Robust	Robust
R-squared	0.0794	0.3312
R-squared (within)	0.0794	–0.1307
R-squared (between)	–0.1789	0.5426
R-squared (overall)	–0.1638	0.5031
F-statistic	0.3793	4.7535
P-value (F-stat)	0.8575	0.0013
Intercept	7.9648 (35.536)	7.9648 (12.733)
PC1	0.1079 (0.2335)	–1.0599 (–4.0895)
PC2	–0.2268 (–0.7382)	0.5008 (2.6300)
PC3	0.4937 (1.1282)	0.2107 (0.5213)
PC4	–0.3040 (–0.2139)	0.2952 (0.6351)
PC5	–0.2029 (–0.2073)	0.1213 (0.2850)
Effects	Entity	

Note: T-stats reported in parentheses.
Source: Authors' calculations

The fixed-effects model, accounting for time-invariant country characteristics, explains 7.9% of the variance in AI adoption (Table 3) but lacks statistical significance, with none of the principal components (PC1 to PC5) significantly predicting AI adoption. The intercept suggests a baseline AI adoption level, yet coefficients for PC1 to PC5 show no significant effects.

Conversely, the random-effects model, assuming individual-specific effects uncorrelated with the explanatory variables, explains 33.1% of the variance and is statistically significant. In this model, PC1 and PC2 emerge as significant predictors: PC1 has a negative impact, indicating that higher values – representing a contrast between mobile internet usage and traditional economic measures – correlate with lower AI adoption. PC2 shows a positive impact, where higher values – indicating economic growth and broadband use – are associated with increased AI adoption, while PCs 3–5 remain insignificant.

The Hausman test supports the random-effects model, confirming its better fit. This model highlights the inverse relationship between PC1 and AI adoption, and the positive association between PC2 (economic growth and broadband) and AI adoption.

4 IMPLICATIONS FOR POLICY, BUSINESS, AND FUTURE RESEARCH

Correlation analysis offers valuable insights for EU policymakers and businesses, underscoring the importance of continuous investment in digital infrastructure, particularly broadband, to fuel economic growth and competitiveness. Policies that promote digital literacy and ensure high-speed internet access are essential for reducing the digital divide, thus enabling more inclusive digital transformation. Understanding the nuanced relationship between economic indicators and digital adoption can further support policies that drive both economic and digital progress, even as these elements may evolve at different rates.

This study highlights the need for further research to explore causal relationships, regional variations, and the impact of policy interventions on economic and digital outcomes. Longitudinal studies would deepen understanding of these shifting dynamics over time, while comparative studies across EU countries could pinpoint effective strategies and areas requiring focused support.

CONCLUSIONS

This study provides a comprehensive empirical analysis of AI adoption among EU enterprises, examining the determinants and sectoral disparities that shape the diffusion of AI technologies. Using a combination of panel data regression, principal component analysis, and cluster analysis, we identify key economic, infrastructural, and regulatory factors influencing AI adoption trends between 2021 and 2023.

The findings indicate a steady rise in AI adoption, with the proportion of enterprises utilizing at least one AI technology increasing from 8% in 2021 to 12% in 2023. However, adoption remains highly asymmetric across firm sizes, with large enterprises (28%) significantly outpacing small (6%) and medium-sized firms (13%), reinforcing the persistent resource and capability gap between SMEs and larger firms. This disparity highlights the need for targeted policy interventions that facilitate SME access to AI technologies through financial incentives, knowledge-sharing platforms, and workforce upskilling initiatives.

Sectoral analysis reveals a pronounced divide in AI adoption patterns. The information and communication sector exhibits the highest adoption rates (25%), followed by professional services (17%), while traditional industries such as manufacturing and logistics remain below 10%. Regression results confirm that AI adoption correlates positively with economic growth and broadband infrastructure but negatively with reliance on mobile internet, suggesting that enterprises with stronger fixed broadband infrastructure are more likely to integrate AI. This underscores the critical role of digital infrastructure investments in enabling AI diffusion, particularly in underdeveloped regions where mobile connectivity remains the primary access mode.

AI acquisition strategies also diverge significantly by firm size. Larger enterprises are more likely to develop AI in-house (39%) or customize commercial AI solutions, whereas SMEs primarily depend on off-the-shelf commercial AI software (53%). These findings highlight the necessity of SME-friendly AI ecosystems, including open-source AI tools, cloud-based AI solutions, and government-backed AI adoption programs to bridge the technological gap.

The regulatory landscape plays a crucial role in shaping AI adoption trajectories across EU member states. Clustering analysis indicates that high-adoption countries (Denmark, Germany, Netherlands) are characterized by strong digital infrastructures and well-defined regulatory frameworks, whereas low-adoption countries (Romania, Bulgaria, Greece) exhibit weaker regulatory alignment and digital capabilities. This divergence suggests that harmonizing AI governance frameworks, strengthening ethical oversight mechanisms, and fostering cross-border regulatory cooperation will be essential to ensuring equitable AI adoption across the EU.

From a policy perspective, our findings reinforce the importance of sustained investment in high-speed broadband infrastructure, AI literacy programs, and regulatory standardization. Given that SMEs face persistent barriers to AI adoption, tailored financial instruments such as AI innovation grants, tax incentives for AI adoption, and industry-specific regulatory support should be prioritized to stimulate broader diffusion.

Future research should expand on these insights by incorporating firm-level characteristics such as workforce digital skills, R&D intensity, and organizational readiness for AI integration. Additionally, longitudinal studies examining the causal impact of AI adoption on firm performance, productivity, and competitiveness would provide deeper insights into the long-term implications of AI-driven transformation in European enterprises.

By bridging the gap between empirical evidence and policy design, this study contributes to the growing discourse on AI adoption and digital transformation in the EU. The findings underscore the urgency of coordinated policy action to mitigate structural disparities in AI uptake and ensure that all enterprises, regardless of size or sector, can fully leverage AI's transformative potential for sustainable economic growth.

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