



**Artificial Intelligence Adoption
in European Enterprises:
Empirical Evidence from Eurostat Data**

Descriptive and Analytical Studies Supporting the AI-ImpactSK Project



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Authors: Anita Romanová, Nora Grisáková, Peter Štetka, Matej Černý, Vladimír Bolek, Zuzana Hajduová, Robert Hanák, Diana Pallérová, Federico Banda, Anna Hamranová, Filip Stovíček, Andriana Baziuk, Vladimír Hojdík, Slavka Šagátová, Simona Kosztanko, Dana Hrušovská, Iveta Kufelová

Edited by: Filip Stovíček, Peter Štetka, Nora Grisáková, Zuzana Hajduová

Reviewers:

doc. Ing. Mojmír Kokles, PhD.

Ing. Terézia Romanová, PhD.

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Foreword

The AI-ImpactSK project — *Empirical Examination of Artificial Intelligence Adoption and its Consequential Impact on Enterprise Performance, Market Dynamics, and Policy Formulation in the Slovak Economy* — aims to comprehensively examine the impact of artificial intelligence adoption across key sectors of the Slovak economy, analysing how AI influences business performance, market dynamics, and innovation diffusion. Funded by the EU NextGenerationEU through the Recovery and Resilience Plan for Slovakia (project No. 09I05-03-V02-00003/2025/VA), the project combines large-scale market surveys, qualitative interviews with AI-adopting firms, comparative international analysis, diffusion forecasting, corporate performance modelling, and targeted knowledge transfer to produce both academic knowledge and actionable policy recommendations. This proceedings volume presents a set of empirical studies that form the analytical foundation for the project's subsequent primary research phases.

Artificial intelligence has ceased to be a distant technological prospect and has become a tangible determinant of competitiveness, productivity, and innovation capacity across the European economy. The pace at which enterprises adopt AI technologies, the barriers they encounter, and the functional domains in which they deploy these tools are questions of immediate relevance to researchers, policymakers, and business leaders alike. Yet despite growing policy attention — most notably the European Union's Digital Decade targets — systematic empirical evidence on enterprise-level AI adoption across EU member states has remained fragmented and methodologically inconsistent.

This proceedings volume addresses that gap. The sixteen studies assembled here draw on harmonized Eurostat data from the Community Survey on ICT Usage and Employment in Enterprises to provide a comprehensive, multi-dimensional portrait of AI adoption in European enterprises. Each article examines a distinct analytical angle — from longitudinal adoption trends and firm-size differentials, through cross-country benchmarking and digital intensity associations, to the adoption of specific AI application domains such as machine learning, generative AI, business process automation, and AI for R&D and innovation. The collection also investigates the structural barriers to adoption, including cost and knowledge constraints, ethical and legal concerns, and the prevalence of AI bias mitigation practices.

A distinctive feature of this volume is its consistent methodological approach. All articles employ descriptive statistical analysis complemented by appropriate inferential tests — including OLS regression, Mann-Kendall trend tests, Spearman rank correlations, chi-square tests of independence, and coefficient-of-variation analyses — applied to officially collected, publicly available Eurostat microdata. This methodological coherence ensures that findings are directly comparable across articles and that the volume as a whole constitutes a unified analytical resource rather than a loosely connected anthology.

The studies presented here form the empirical foundation upon which subsequent phases of the AI-ImpactSK project will build. The project's broader agenda encompasses primary market surveys, qualitative interviews with AI-adopting firms, policy formulation, comparative international analysis, diffusion forecasting, and corporate performance modelling. By establishing a rigorous evidence base from secondary data, this volume ensures that the project's later primary research is informed by a thorough understanding of the existing landscape of enterprise AI adoption in Europe.

We trust that this collection will serve not only as a reference for the academic community but also as a practical resource for policymakers designing AI adoption support mechanisms and for enterprise leaders navigating their own digital transformation journeys. The empirical patterns documented in these pages — the persistent size-class gaps, the cross-country heterogeneity, the uneven diffusion of ethical AI practices — represent both challenges to be addressed and opportunities to be seized as

Europe pursues its ambition of becoming a global leader in trustworthy and competitive artificial intelligence.

The Editors

Bratislava, March 2026

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AI Technology Adoption Trends Across European Enterprises: A Eurostat-Based Four-Observation-Year Analysis

Anita Romanová¹ and Nora Grisáková²

¹ Bratislava University of Economics and Business, Faculty of Business Management, Dolnozemská cesta 1, 852 35 Bratislava, Slovakia (EU); e-mail: anita.romanova@euba.sk

² Bratislava University of Economics and Business, Faculty of Business Management, Dolnozemská cesta 1, 852 35 Bratislava, Slovakia (EU); e-mail: nora.grisakova@euba.sk

Abstract

As artificial intelligence becomes a central component of enterprise digital transformation, monitoring the pace and unevenness of its adoption has become increasingly important for European policymakers and business leaders. This article examines enterprise AI adoption using Eurostat's isoc_eb_ai dataset, focusing on the indicator E_AI_TANY, which measures the percentage of enterprises using at least one AI technology. The analysis covers four Eurostat observation years - 2021, 2023, 2024, and 2025 - and constructs an unweighted average across available country and enterprise-size observations rather than using Eurostat's official EU27 aggregate. The filtered dataset contains 685 available observations across 36 Eurostat reporting geographies, five enterprise-size classes, and four observation years. The constructed annual average increased from 11.19% in 2021 to 26.53% in 2025, representing a gain of 15.34 percentage points. The increase is concentrated mainly after 2023, indicating a substantial descriptive acceleration in enterprise AI adoption. However, formal inference remains limited: OLS regression using calendar year as the predictor indicates a positive but not conventionally significant trend ($\beta = 3.73$ percentage points per year, $R^2 = 0.809$, $p = 0.101$), and the Mann-Kendall test likewise does not reach the 0.05 threshold ($Z = 1.698$, $p = 0.089$). Slovakia remains below the constructed annual average in each observation year but follows the same upward pattern, increasing from 8.08% in 2021 to 23.46% in 2025. The findings document substantial descriptive growth and persistent heterogeneity in enterprise AI adoption while emphasizing the limits of statistical confirmation with a short and unevenly spaced time series.

1. Introduction

Artificial intelligence has moved rapidly from a specialized technological capability to a visible component of enterprise digital transformation. For European policymakers, this development is directly connected to the European Union's Digital Decade agenda, which places advanced digital technology adoption at the center of competitiveness, innovation, and productivity policy. For enterprise managers, AI adoption is increasingly relevant not only as a technical decision but also as a strategic question involving organizational readiness, skills, data infrastructure, and the ability to translate new technologies into operational value.

Despite this growing policy and managerial relevance, empirical evidence on the trajectory of enterprise AI adoption remains difficult to interpret. Cross-sectional indicators can show how widely AI is used in a given year, but they provide limited insight into whether adoption is accelerating, whether increases are evenly distributed, and how much confidence can be placed in apparent time trends. Longitudinal analysis is therefore needed, but available harmonized data remain short and unevenly spaced. In the Eurostat isoc_eb_ai dataset, comparable observation years for the selected AI indicator are 2021, 2023, 2024, and 2025, with no 2022 observation. This creates an analytical challenge: the data are sufficiently informative to document descriptive change, but they are too limited to support strong confirmatory claims about the statistical significance or precise shape of the diffusion trajectory.

This article examines the trajectory of enterprise AI adoption using Eurostat's isoc_eb_ai dataset and the indicator E_AI_TANY, which captures the percentage of enterprises using at least one AI technology. The analysis constructs an unweighted average across available country and enterprise-size

observations. This measure is not Eurostat's official EU27 aggregate; instead, it is designed to describe the average pattern across the available reporting geographies and enterprise-size classes in the filtered dataset. The resulting dataset contains 685 available observations across 36 Eurostat reporting geographies, five enterprise-size classes, and four observation years.

The study has three objectives. First, it documents the descriptive evolution of the constructed annual average between 2021 and 2025. Second, it assesses whether the observed increase can be treated as statistically significant when calendar year is used as the time variable. Third, it examines heterogeneity across observations and situates Slovakia within the same country-size observation framework. This Slovak focus is important because the article is written in the context of research on AI adoption and digital transformation in Slovakia, where questions of absorptive capacity, enterprise readiness, and convergence with broader European patterns are especially relevant.

The contribution of the article is therefore both empirical and methodological. Empirically, it shows that the constructed annual average increased substantially, from 11.19% in 2021 to 26.53% in 2025, with most of the increase occurring after 2023. Slovakia follows the same upward pattern but remains below the constructed annual average in each observation year. Methodologically, the article demonstrates the importance of distinguishing between descriptive growth and statistical confirmation when working with short time series. OLS regression using calendar year as the predictor indicates a positive but not conventionally significant trend, and the Mann-Kendall test also falls short of the 0.05 threshold. The findings should therefore be interpreted as evidence of substantial descriptive growth and persistent heterogeneity rather than as conclusive proof of a statistically significant longitudinal trend.

The remainder of this article is structured as follows. Section 2 develops the theoretical background, drawing on innovation diffusion theory, the Technology-Organization-Environment framework, and absorptive capacity theory to situate the empirical investigation. Section 3 reviews the relevant literature across three thematic clusters: enterprise AI adoption, barriers and drivers of digital transformation, and empirical measurement of digital diffusion. Section 4 describes the data source, construction of the unweighted country-size observation dataset, and statistical methods employed. Section 5 reports the descriptive, year-over-year, and inferential results, including cross-sectional variation and Slovakia's positioning. Section 6 discusses the findings in relation to theory and prior literature and draws out policy and managerial implications. Section 7 concludes by summarizing the contribution and proposing future research directions.

2. Theoretical Background

The theoretical foundations of this study rest on three complementary frameworks that together address how, why, and at what rate organizations integrate novel technologies into their operations: innovation diffusion theory, the Technology-Organization-Environment (TOE) framework, and absorptive capacity theory.

Innovation diffusion theory, most comprehensively articulated by Rogers (2003), posits that the adoption of any new technology within a social system follows a predictable S-shaped trajectory over time. New technologies initially attract a small cohort of innovators and early adopters, after which the pace of uptake accelerates sharply as social proof accumulates, costs decline, and institutional legitimacy strengthens; eventually, adoption plateaus as saturation among susceptible adopters is reached. Rogers (2003) identified five characteristics of innovations that influence adoption speed — relative advantage, compatibility, complexity, trialability, and observability — and these characteristics apply with particular force to AI technologies, which offer substantial relative advantages in process efficiency and decision quality but also impose considerable compatibility and complexity challenges for less digitally mature organizations. The S-curve model provides the theoretical baseline against which the temporal patterns observed in the Eurostat data can be assessed, though it must be noted that four observation points are insufficient to confirm or refute S-curve dynamics with statistical confidence; the characterization of observed patterns as consistent with S-curve theory should be read as theoretically informed conjecture rather than confirmed inference.

The Technology-Organization-Environment (TOE) framework, introduced by Tornatzky and Fleischer (1990), extends the focus of adoption analysis from individual perceptions to the organizational and environmental context. In the TOE model, technology adoption decisions are jointly shaped by the technological context (the internal and external technologies available to the firm), the organizational context (characteristics such as firm size, managerial structure, and resource availability), and the environmental context (the industry structure, competitive dynamics, and regulatory environment). This framework is particularly well-suited to the present study because the EU panel data encompass enterprises operating across diverse national regulatory environments and at varying scales, producing the kind of multi-level heterogeneity that TOE predicts and explains. Empirical applications of the TOE framework have confirmed its explanatory relevance for digital technology adoption across multiple national and sectoral contexts (Omrani et al., 2022), and it serves here as the theoretical lens through which cross-national disparities in adoption rates are interpreted.

Absorptive capacity, introduced by Cohen and Levinthal (1990), refers to the ability of an organization to recognize the value of new external information, assimilate it, and apply it to commercial ends. Critically, absorptive capacity is not uniformly distributed across the enterprise population; it is a cumulative capability that is largely a function of prior related knowledge and existing investment in human capital and research activities. This theoretical construct is directly relevant to the observed heterogeneity in EU enterprise AI adoption: organizations with higher baseline digital competencies are better positioned to recognize and integrate AI tools rapidly, whereas those lacking such prior knowledge face structural barriers that compound over time. Grashof and Kopka (2022) applied this reasoning specifically to AI, demonstrating that AI-related knowledge structures are unevenly distributed between SMEs and large firms, contributing to persistent adoption gaps. This insight also resonates with the resource-based view articulated by Barney (1991), which holds that sustainable competitive advantage derives from resources — including digital and knowledge assets — that are valuable, rare, and difficult to imitate.

Together, these frameworks generate a theoretically coherent account of the adoption patterns the present study expects to observe: a directional upward trend in EU enterprise AI adoption, an acceleration phase broadly consistent with S-curve dynamics, persistent cross-national heterogeneity reflecting differential organizational and environmental contexts, and a widening absorption gap between resource-rich and resource-constrained enterprises. Building on these theoretical foundations, the present study applies this integrated lens to the four-time-point Eurostat panel to assess whether the observed trajectory of EU enterprise AI adoption is consistent with S-curve diffusion dynamics and to quantify the heterogeneity that diffusion theory and the TOE framework predict.

3. Literature Review

Generative and applied AI technologies are increasingly recognized as transformative organizational assets, yet adoption rates vary substantially across firm size, sector, and national context, with organizational readiness and managerial cognition serving as key moderators of uptake speed. The publication of large language model applications in late 2022 prompted a wave of scholarly attention to how AI adoption reshapes business model logic. Kanbach et al. (2023) argued that generative AI represents a discontinuous rather than incremental shift in organizational AI engagement, enabling firms to redesign value creation mechanisms rather than merely automate existing workflows. Similarly, Mariani and Dwivedi (2024) outlined a future research agenda in which generative AI intersects with innovation management across ten major themes, underscoring the breadth of organizational functions now potentially subject to AI-mediated transformation.

The heterogeneity of adoption across the enterprise population, however, is a persistent empirical finding that complicates any optimistic narrative of uniform diffusion. Singh et al. (2024) demonstrated that the relationship between generative AI applications and organizational performance is mediated by the firm's capacity for explorative and exploitative innovation and moderated by ethical dilemmas and environmental dynamism, suggesting that high-level adoption statistics can mask substantial variation in depth and quality of integration. Al-Surmi et al. (2021) provided empirical evidence that AI-based decision-making frameworks improve operational performance, but the degree of improvement is

conditioned on the degree of strategic alignment between marketing and information technology functions - an alignment more readily achievable in larger, more integrated enterprises. These findings collectively underscore that the aggregate adoption rate documented in administrative datasets represents a substantial simplification of a highly differentiated organizational phenomenon.

3.1 Drivers and Barriers of Digital Transformation in SMEs and Large Firms

Digital transformation is shaped by firm-level resource endowments, absorptive capacity, and enabling Industry 4.0 technologies; resource-based constraints disproportionately hinder smaller enterprises, producing persistent heterogeneity in adoption levels across the enterprise population. Omrani et al. (2022) applied the TOE framework to a dataset of over 15,000 European SMEs, identifying regulatory environment, managerial capability, and access to digital infrastructure as the primary determinants of digital technology adoption intensity. Their ordered logit results highlighted the compounding disadvantage faced by micro-enterprises that lack both the financial resources and the managerial knowledge base to evaluate and implement digital technologies effectively. This finding is consistent with the resource-based view (Barney, 1991), which predicts that resource heterogeneity among firms generates durable performance and capability differentials.

Martinelli et al. (2020) examined the enabling technologies of Industry 4.0 and found that technologies such as advanced robotics, cloud computing, and AI are not adopted in isolation but as complementary bundles; firms that invest in one enabling technology are significantly more likely to invest in others, creating a technological complementarity effect that accelerates diffusion among already-digitized enterprises while deepening the gap for late adopters. Ghobakhloo et al. (2024) extended this analysis to the emerging Industry 5.0 paradigm, arguing that the sustainability and human-centric values embedded in the next industrial wave will impose additional capability demands on enterprises, further differentiating those with accumulated digital absorptive capacity from those without. The implication for the present study is that the cross-national heterogeneity observed in the Eurostat data is not a transient feature of early adoption dynamics but a structurally embedded pattern that may persist or even intensify as AI applications become more sophisticated.

Resource constraints appear with particular force when examining Central and Eastern European (CEE) member states, which systematically show lower digital transformation intensity than their Western European counterparts. Nucci et al. (2023) found that, among Italian firms, digital technology adoption - including AI - was associated with measurable total factor productivity gains, but their sample was skewed toward medium and large firms with prior digital investment histories. The analytical distance between a Western European country such as Italy and CEE economies such as Slovakia is considerable: the baseline absorptive capacity, managerial skills, and financial slack required to initiate AI-enabled transformation may be less uniformly available in CEE contexts, meaning that the productivity-motivated adoption pattern Nucci et al. (2023) document may not transfer straightforwardly to member states at lower stages of digital maturity. This limitation in the available literature underscores a gap in CEE-specific empirical evidence on AI adoption that future research should address directly.

3.2 Measurement and Empirical Assessment of Digital and AI Diffusion

Eurostat and comparable survey instruments provide robust cross-national benchmarks for digital technology diffusion, while empirical studies document uneven adoption patterns that can be interpreted through the lens of innovation diffusion theory. Eurostat (2024) documents in its methodological manual the rigorous survey design, stratified sampling approach, and harmonized variable definitions that underpin the Community Survey on ICT Usage and E-Commerce in Enterprises, making its AI adoption indicators among the most comparable cross-national measures currently available. The *isoc_eb_ai* dataset, from which the present study draws, provides harmonized observations on AI technology usage across countries, enterprise-size classes, and observation years, enabling comparative analysis that would be difficult to assemble from nationally administered surveys alone.

Gerlich (2023) conducted a multi-country perception study of AI acceptance among over a thousand respondents, finding that alignment with Trustworthy AI principles promoted by the European

Commission was positively correlated with reported AI adoption intentions, pointing to a regulatory legitimacy mechanism that may support enterprise uptake as governance frameworks mature and become operationalized. Schwabe and Castellacci (2020) approached digital diffusion measurement from the labor market side, finding that automation adoption at the firm level affects worker job satisfaction - an indirect indicator of technology uptake that complements enterprise-level survey data. Grashof and Kopka (2022) specifically quantified the relationship between AI-related knowledge intensity and radical innovation output, finding significant differences between SMEs and large firms - a pattern of structured inequality that administrative survey data can document at scale but that requires firm-level panel analysis to fully disentangle. Akande et al. (2019), examining the relationship between technology deployment and environmental sustainability across European cities, provided contextual evidence of the spatially uneven distribution of technology uptake, suggesting that geographic proximity and shared institutional environments may shape digital adoption trajectories in ways that aggregate national statistics do not fully capture.

Despite this body of evidence, there remains a need for longitudinal quantitative analyses of enterprise AI adoption using harmonized official data that distinguish descriptive change from statistical confirmation and candidly address the methodological limits of inference with short time series. This article addresses that need by constructing a transparent unweighted country-size observation series from Eurostat data and evaluating both the magnitude and inferential limits of the observed change.

4. Methodology

The empirical analysis is based on Eurostat's dataset `isoc_eb_ai` - Artificial intelligence by size class of enterprise. The selected indicator is `E_AI_TANY`, which measures the percentage of enterprises using at least one AI technology. The unit of measurement is the percentage of enterprises. The analysis uses the NACE aggregate covering all activities except agriculture, forestry and fishing, and mining and quarrying, without the financial sector.

Four observation years are available for the selected indicator in the dataset used for this study: 2021, 2023, 2024, and 2025. There is no observation for 2022. This missing year is important for interpretation because the interval between 2021 and 2023 spans two calendar years, whereas the intervals between 2023 and 2024 and between 2024 and 2025 each span one year.

Step 1 — Dataset: The empirical analysis is based on Eurostat's dataset `isoc_eb_ai` - Artificial intelligence by size class of enterprise. The selected indicator is `E_AI_TANY`, which measures the percentage of enterprises using at least one AI technology. The unit of measurement is the percentage of enterprises. The analysis uses the NACE aggregate covering all activities except agriculture, forestry and fishing, and mining and quarrying, without the financial sector.

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Step 2 — Dataset Construction: The filtered dataset contains observations across 36 Eurostat reporting geographies and five enterprise-size classes. After excluding suppressed or unavailable non-numeric cells, the analytical dataset contains 685 available country-enterprise-size observations across the four observation years. These observations form the basis for the descriptive statistics and for the construction of the annual analytical series.

The dataset should not be interpreted as a country-year panel of statistically independent observations. Country and enterprise-size observations are nested within the Eurostat data structure, and the same reporting geographies and size categories appear repeatedly across years. The purpose of the filtered dataset is therefore descriptive: it characterizes the distribution of AI adoption rates across available reporting geographies and enterprise-size classes, rather than providing a firm-level sample or a fully independent panel suitable for causal inference.

Step 3 — Construction of the Annual Unweighted Average: For each observation year, an annual value was calculated as the unweighted mean of all available country-enterprise-size observations in that year. Each available observation contributes equally to the annual mean, regardless of the number of enterprises represented by a country or enterprise-size class. The resulting measure is referred to in this article as an unweighted average across available country and enterprise-size observations.

This measure is conceptually different from Eurostat's official EU27 aggregate. The official aggregate represents a population-weighted statistical measure for the European Union, whereas the measure used here summarizes the average position of available reporting-geography and enterprise-size observations in the filtered dataset. This distinction is important because the constructed average gives equal weight to all available observations and is therefore more suitable for describing cross-sectional dispersion and comparative patterns than for representing the population-weighted EU enterprise total.

The number of available observations differs slightly by year because some cells are unavailable or suppressed in Eurostat. The annual series is based on 175 observations in 2021, 169 observations in 2023, 168 observations in 2024, and 173 observations in 2025. These four annual means constitute the time series used for trend analysis.

Step 4 — Descriptive and Year-over-Year Analysis: Descriptive statistics were calculated across all 685 available observations. These include the mean, median, standard deviation, standard error, 95% confidence interval, minimum, maximum, first and third quartiles, interquartile range, and coefficient of variation. These statistics are used to assess the overall distribution of AI adoption and the degree of heterogeneity across reporting geographies and enterprise-size classes.

Year-over-year changes were then calculated for the three available intervals: 2021→2023, 2023→2024, and 2024→2025. Both absolute changes in percentage points and relative percentage changes were computed. Because the first interval spans two calendar years while the latter two intervals each span one year, the changes are interpreted as interval-level descriptive changes rather than strictly comparable annual growth rates.

To assess whether the observed descriptive increase can be treated as a statistically significant time trend, two complementary procedures were applied to the four-point annual series.

First, Ordinary Least Squares (OLS) regression was estimated with calendar year as the numeric predictor and the constructed annual unweighted average as the dependent variable. Calendar year was used because the observation points are unevenly spaced. This preserves the two-year interval between 2021 and 2023 and avoids treating all observation intervals as equal. A sequential survey-wave index was not used, because such coding would assign the same temporal distance to 2021→2023, 2023→2024, and 2024→2025 despite their different calendar lengths.

Second, the non-parametric Mann-Kendall trend test was applied to the same annual series. This test assesses whether the series shows a monotonic upward or downward pattern without assuming a linear functional form. It is useful as a robustness check for trend direction, but with only four observations its statistical power is necessarily limited.

Both inferential procedures are interpreted cautiously. With only four time points, the OLS model has only two residual degrees of freedom, and the Mann-Kendall test has a highly discrete p-value structure. Therefore, the statistical tests are used to distinguish descriptive increase from formal statistical confirmation, not to provide strong causal or predictive evidence. The results are interpreted as indicative of the observed trajectory under the limitations of a short and unevenly spaced time series.

Slovakia is analyzed within the same country-enterprise-size observation framework as the full dataset. For each observation year, Slovakia's value is calculated as the unweighted average across the available enterprise-size classes for Slovakia. These annual Slovak averages are then compared with the constructed annual average across all available reporting geographies and enterprise-size observations. This comparison is descriptive and should not be interpreted as a population-weighted comparison with Eurostat's official EU aggregate.

5. Results

The filtered dataset contains 685 available country-enterprise-size observations for the indicator E_AI_TANY across the four observation years. Across all available observations, the mean AI adoption rate is 17.36% (SD = 14.88), with a median of 12.26%. The descriptive 95% interval around the mean is [16.24, 18.47], but it should be interpreted cautiously because the observations are not independent firm-level records. Values range from 0.24% to 79.40%, with an interquartile range of 16.05 percentage points (Q1 = 6.98%, Q3 = 23.03%). The coefficient of variation is 85.72%, indicating substantial dispersion across observations.

The divergence between the mean and median indicates a right-skewed distribution: many observations remain at relatively low adoption levels, while a smaller number of high-adoption country-size combinations pull the mean upward. This confirms that AI adoption is not evenly distributed across the available Eurostat reporting geographies and enterprise-size classes. The wide range and large interquartile spread also suggest that a single aggregate value is insufficient to characterize the full distribution of enterprise AI adoption.

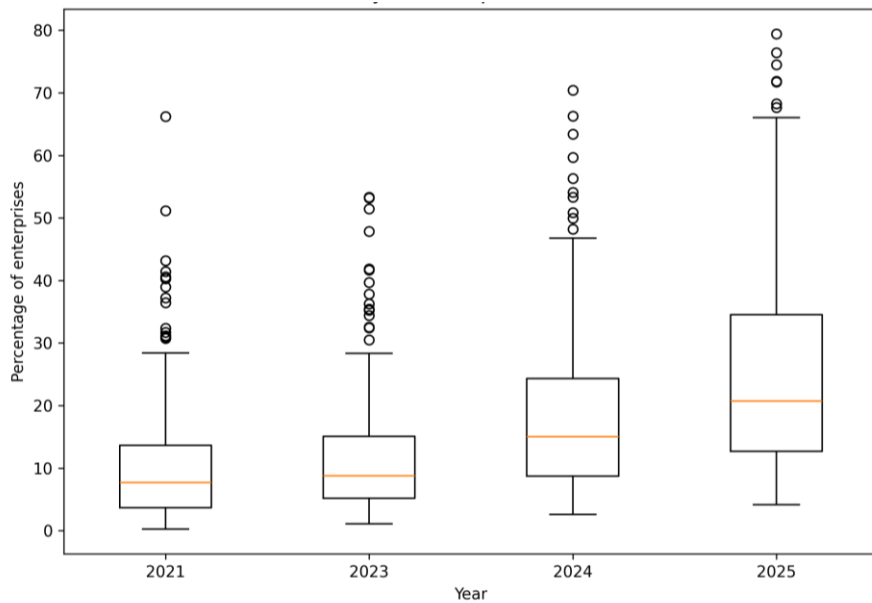


Figure 1. Distribution of enterprises using at least one AI technology across available country and enterprise-size observations, by year.

Table 1. Descriptive Statistics

Statistic	Value
n	685
mean	17.36
median	12.26
std	14.88
sem	0.569
CI95_low	16.24
CI95_high	18.47
min	0.24
max	79.40
Q1	6.98
Q3	23.03
IQR	16.05
CV_%	85.72

5.1 Annual Unweighted Average and Trend Analysis

The annual unweighted average across available country and enterprise-size observations increased substantially over the observation window. As shown in Figure 2, it rose from 11.19% in 2021 to 26.53% in 2025, corresponding to a cumulative change of 15.34 percentage points. In relative terms, the 2025 value is approximately 137.2% higher than the 2021 value.

The increase was not evenly distributed across the observation intervals. From 2021 to 2023, a two-year interval, the annual average increased only from 11.19% to 12.40%, a gain of 1.21 percentage points (+10.84%). From 2023 to 2024, it rose sharply by 6.94 percentage points (+55.96%), reaching 19.34%. From 2024 to 2025, it increased by a further 7.19 percentage points (+37.20%), reaching 26.53%. This pattern indicates that most of the observed increase is concentrated after 2023.

The missing 2022 observation remains important for interpretation. Because the first interval spans two calendar years while the later intervals span one year each, the apparent flatness of the early period and the sharpness of the post-2023 acceleration should be interpreted cautiously. The data show a clear descriptive increase, but the precise timing of any acceleration or inflection point cannot be established with only four unevenly spaced observations.

OLS regression using calendar year as the predictor yields a positive slope of $\beta = 3.73$ percentage points per year ($R^2 = 0.809$, $p = 0.101$). The slope indicates a substantial upward descriptive trend, but the p -value does not reach the conventional 0.05 threshold. The non-parametric Mann-Kendall test likewise indicates a monotonic upward pattern but does not reach conventional statistical significance ($Z = 1.698$, $p = 0.089$). Taken together, the inferential tests support the existence of a strong descriptive increase, but they do not provide robust statistical confirmation of a significant time trend. The results should therefore be interpreted as evidence of substantial observed growth in AI adoption rather than as conclusive evidence of a statistically significant longitudinal trend.

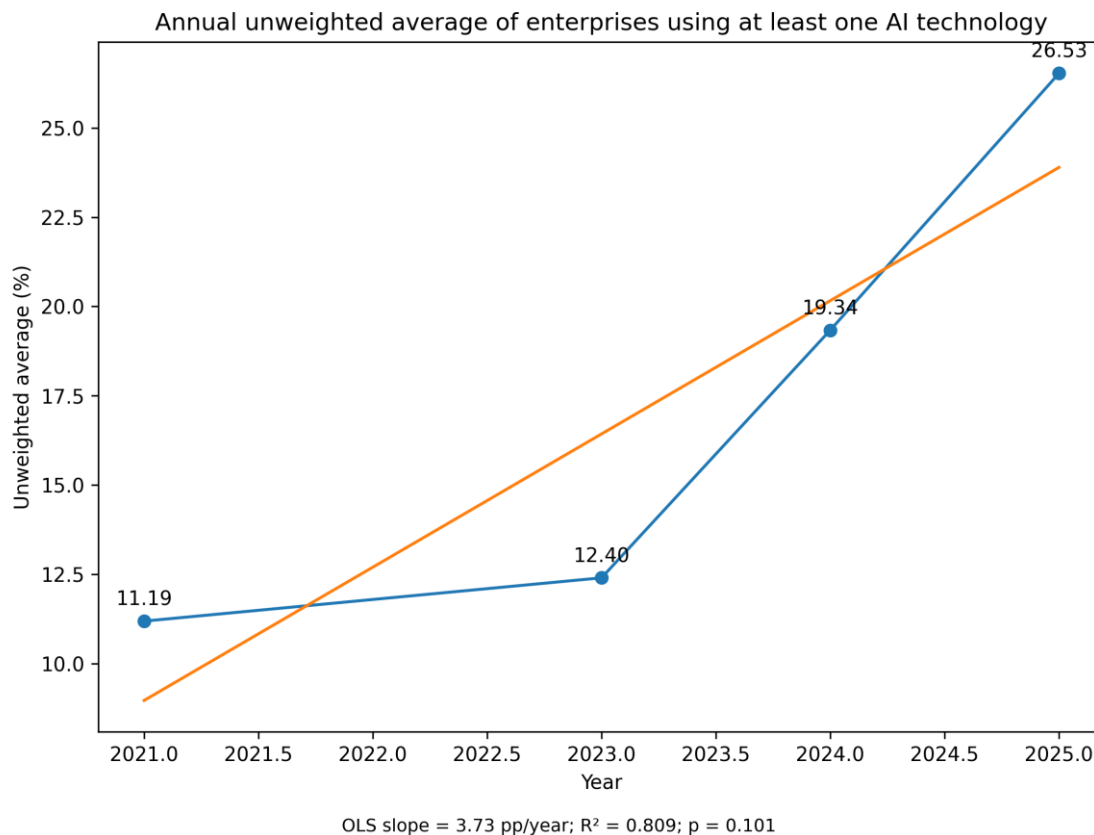


Figure 2. Annual unweighted average of enterprises using at least one AI technology, with calendar-year OLS trend line. The line is fitted using calendar year as the numeric predictor, preserving the two-year interval between 2021 and 2023.

Table 2. Year-over-Year Changes - Enterprises Using at Least One AI Technology

From	To	Value prev (%)	Value curr (%)	Change (pp)	Change (%)
2021	2023	11.19	12.40	1.21	10.84
2023	2024	12.40	19.34	6.94	55.96
2024	2025	19.34	26.53	7.19	37.20

5.2 Cross-Sectional Variation and Slovakia's Positioning

The descriptive statistics document not only an upward annual pattern but also persistent heterogeneity across available reporting geographies and enterprise-size classes. The range from 0.24% to 79.40% indicates that the constructed annual average masks substantial variation across observations. This heterogeneity is consistent with theoretical expectations that AI adoption is shaped by organizational size, digital maturity, resource availability, and national or regional enabling conditions.

Slovakia is retained as a focal country because of the article's national research context. Within the same unweighted country-enterprise-size observation framework used for the main analysis, Slovakia contributes 20 available observations: five enterprise-size classes across four observation years. Across these observations, Slovakia's mean adoption rate is 14.10%, compared with 17.36% for the full filtered dataset. Slovakia is therefore 3.26 percentage points below the overall unweighted average across available reporting geographies and enterprise-size observations.

Slovakia follows the same broad upward trajectory as the full dataset, increasing from 8.08% in 2021 to 23.46% in 2025. The cumulative increase amounts to 15.38 percentage points, which is almost identical in absolute terms to the overall constructed average increase of 15.34 percentage points. However, Slovakia remains below the overall annual average in each observation year. The gap is 3.11 percentage points in 2021, 2.42 percentage points in 2023, 4.46 percentage points in 2024, and 3.07 percentage points in 2025. This pattern, visualized in Figure 3, suggests that Slovakia participates in the general post-2023 acceleration but does not converge fully with the broader unweighted country-size average.

Table 3. Slovakia's Position Relative to the Constructed Annual Average

Year	Slovakia average (%)	Constructed annual average (%)	Difference (pp)
2021	8.08	11.19	-3.11
2023	9.97	12.40	-2.42
2024	14.88	19.34	-4.46
2025	23.46	26.53	-3.07

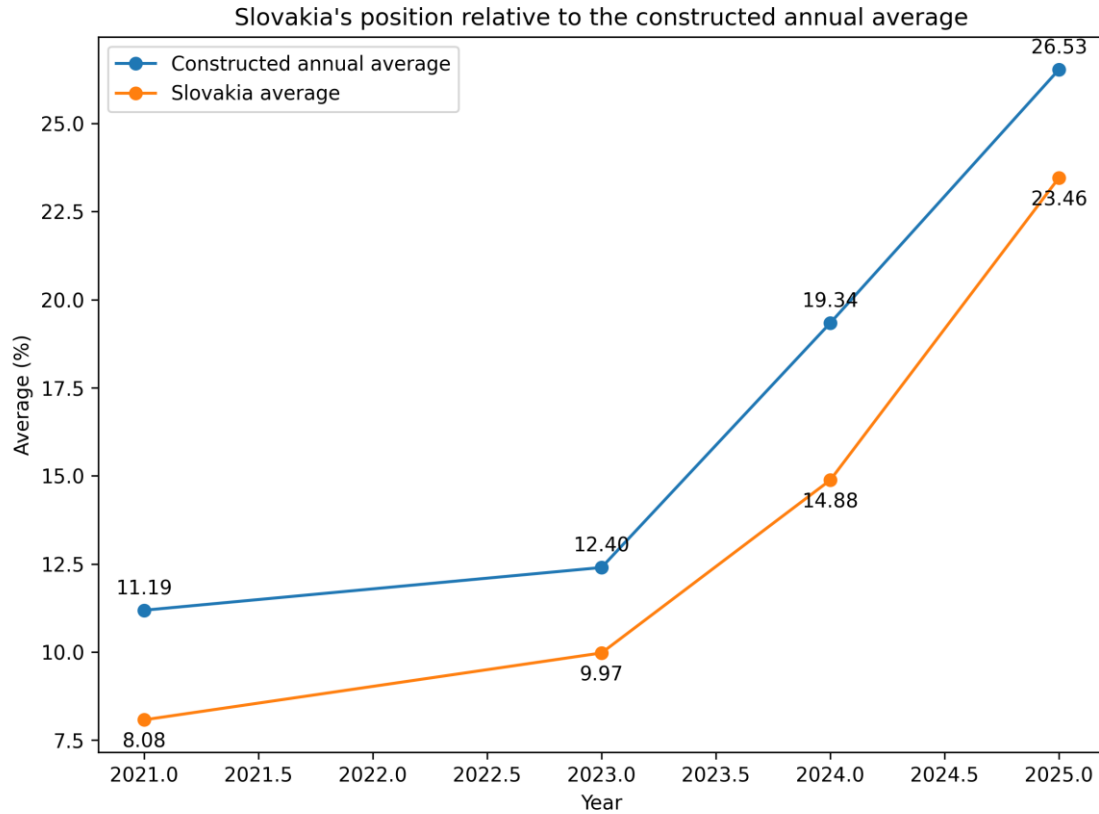


Figure 3. Slovakia's annual unweighted average compared with the constructed annual average across all available country and enterprise-size observations.

Table 4. Year-over-Year Changes in Slovakia's Unweighted AI Adoption Average

From	To	Value prev (%)	Value curr (%)	Change (pp)	Change (%)
2021	2023	11.19	12.40	1.21	10.84
2023	2024	12.40	19.34	6.94	55.96
2024	2025	19.34	26.53	7.19	37.20

These results support the interpretation that Slovakia belongs to the lower-adoption part of the observed distribution, while also showing a marked increase in enterprise AI adoption after 2023. This positioning is consistent with the absorptive capacity framework, which emphasizes the role of prior digital knowledge and organizational readiness, and with the TOE framework's emphasis on environmental and organizational conditions shaping adoption decisions.

6. Discussion

The results indicate a substantial descriptive increase in enterprise AI adoption across the constructed Eurostat-based measure. The unweighted annual average across available country and enterprise-size observations increased from 11.19% in 2021 to 26.53% in 2025, a gain of 15.34 percentage points. The increase was especially pronounced after 2023, with the annual average rising from 12.40% in 2023 to 19.34% in 2024 and to 26.53% in 2025. This pattern suggests that enterprise AI adoption entered a more dynamic phase in the later part of the observation window.

At the same time, the inferential results require caution. OLS regression using calendar year as the predictor yields a positive but not conventionally significant slope ($\beta = 3.73$ percentage points per year, $R^2 = 0.809$, $p = 0.101$). The Mann-Kendall test also does not reach the 0.05 significance threshold ($Z = 1.698$, $p = 0.089$). The appropriate interpretation is therefore not that a statistically significant longitudinal trend has been confirmed, but rather that the available Eurostat observations show a strong

descriptive increase that cannot be formally confirmed at conventional significance levels because the time series contains only four unevenly spaced observations.

This distinction is central to the article's contribution. In policy and managerial discussions, rapid increases in observed adoption rates are often treated as evidence of a clear trend. The present analysis shows why such interpretation should be qualified. The 2021-2025 increase is large in substantive terms, but the absence of a 2022 observation and the very small number of annual data points limit the strength of statistical inference. The results are therefore best understood as an empirically grounded monitoring signal rather than as confirmatory evidence of a stable long-term trajectory.

The findings can nevertheless be interpreted meaningfully through innovation diffusion theory. The concentration of growth after 2023 is consistent with the idea that AI adoption may be moving beyond an early-adopter phase toward broader organizational diffusion. This timing also corresponds to a period in which generative AI became more visible and accessible to enterprises. However, the available data do not allow the study to confirm S-curve dynamics or to identify an inflection point. The diffusion interpretation should therefore remain theoretical and descriptive. It helps explain the pattern, but it should not be presented as statistically proven.

The high dispersion across observations supports the relevance of the Technology-Organization-Environment framework and absorptive capacity theory. AI adoption is unlikely to depend only on the availability of AI tools. It is also shaped by enterprise size, digital skills, data infrastructure, managerial readiness, sectoral opportunities, and the broader national or regional environment. The descriptive statistics show a right-skewed distribution, with many observations at lower adoption levels and a smaller number of high-adoption observations pulling the mean upward. This indicates that average growth coexists with persistent heterogeneity.

Slovakia's positioning reinforces this interpretation. Slovakia's unweighted average increased from 8.08% in 2021 to 23.46% in 2025, which represents a substantial increase of 15.38 percentage points. In absolute terms, this increase is very close to the overall constructed average increase of 15.34 percentage points. However, Slovakia remains below the constructed annual average in every observation year. The gap does not disappear over the observation window: Slovakia is 3.11 percentage points below the average in 2021, 2.42 percentage points below it in 2023, 4.46 percentage points below it in 2024, and 3.07 percentage points below it in 2025. This suggests that Slovakia is participating in the broader increase in enterprise AI adoption but has not fully converged with the average level of the full filtered dataset.

From a policy perspective, this finding is important. A general increase in AI adoption does not necessarily imply convergence across countries or enterprise groups. If countries or enterprise-size categories with lower initial adoption increase at a similar absolute pace as the overall average, their relative position may remain largely unchanged. Policy measures should therefore focus not only on increasing adoption in aggregate but also on reducing persistent capability gaps. In the Slovak context, this points to the importance of targeted support for enterprise AI readiness, especially among smaller and less digitally mature firms.

Relevant policy instruments may include practical AI adoption programmes for SMEs, subsidized pilot projects, advisory services, access to shared expertise, sector-specific use-case demonstrations, and training focused on data readiness and managerial understanding of AI. These measures are consistent with the absorptive capacity perspective: enterprises are more likely to adopt and benefit from AI when they have the prior knowledge, skills, and organizational routines needed to recognize and apply new technologies. Without such capacity-building, the observed post-2023 acceleration may benefit already prepared enterprises more than those at risk of falling behind.

For enterprise managers, the results suggest that AI adoption should be treated as an organizational capability-building process rather than a one-off technology purchase. The observed increase after 2023 indicates that AI is becoming more common in the enterprise environment, but the variation across observations shows that adoption remains uneven. Managers should therefore begin with a realistic assessment of internal readiness: data availability, digital skills, process maturity, governance arrangements, and potential use cases. For smaller firms, collaboration with external partners - including

technology providers, universities, business associations, and public support programmes - may be essential for overcoming resource and knowledge constraints.

The study also has methodological implications. First, it shows the importance of clearly distinguishing a constructed unweighted average from Eurostat's official EU27 aggregate. These measures answer different questions and should not be used interchangeably. Second, it shows that with only four unevenly spaced annual observations, statistical tests should be interpreted as cautious diagnostic tools rather than as strong confirmatory evidence. Third, it demonstrates that even limited harmonized data can provide useful monitoring insights when the analytical object is defined transparently and the limits of inference are explicitly acknowledged.

Several limitations should be noted. The constructed average gives equal weight to all available country and enterprise-size observations, which means that it does not reflect the population-weighted structure of enterprises across Europe. The dataset also contains suppressed or unavailable cells, and the number of available observations varies by year. The time series is short and lacks a 2022 observation, limiting inference about the timing and shape of acceleration. Finally, the analysis is descriptive and does not identify causal drivers of adoption. Future research should extend the time series as new Eurostat waves become available, examine enterprise-size and sectoral differences in greater detail, and link AI adoption indicators to performance outcomes such as productivity, innovation, or competitiveness.

7. Conclusion

This study examined enterprise AI adoption using Eurostat's `isoc_eb_ai` dataset and the indicator `E_AI_TANY`, which measures the percentage of enterprises using at least one AI technology. The analysis covered four observation years - 2021, 2023, 2024, and 2025 - and constructed an unweighted average across available country and enterprise-size observations. The final analytical dataset contained 685 available observations across 36 Eurostat reporting geographies and five enterprise-size classes.

The findings show a substantial descriptive increase in enterprise AI adoption. The constructed annual average rose from 11.19% in 2021 to 26.53% in 2025, representing an increase of 15.34 percentage points. The largest changes occurred after 2023, indicating that the later part of the observation window was characterized by faster observed uptake. Descriptive statistics also show substantial heterogeneity across observations, with a right-skewed distribution and wide variation between low- and high-adoption cases.

However, the inferential results do not support a strong claim of statistical confirmation. OLS regression using calendar year as the predictor produced a positive but not conventionally significant result ($\beta = 3.73$ percentage points per year, $R^2 = 0.809$, $p = 0.101$). The Mann-Kendall test likewise did not reach the 0.05 significance threshold ($Z = 1.698$, $p = 0.089$). The study therefore concludes that enterprise AI adoption shows substantial descriptive growth, but that the available four-point, unevenly spaced time series is insufficient for confirming a statistically significant longitudinal trend.

Slovakia follows the broader upward pattern but remains below the constructed annual average in each observation year. Its average increased from 8.08% in 2021 to 23.46% in 2025, an increase of 15.38 percentage points. This suggests that Slovakia is participating in the broader increase in AI adoption, while its relative position remains below the overall constructed benchmark. The Slovak case therefore illustrates an important policy point: rapid aggregate growth does not automatically imply convergence.

The article contributes to the measurement of enterprise AI diffusion in three ways. First, it provides a transparent Eurostat-based longitudinal benchmark for AI adoption across country and enterprise-size observations. Second, it explicitly distinguishes the constructed unweighted average used in the analysis from Eurostat's official EU27 aggregate. Third, it demonstrates the importance of separating descriptive growth from statistical confirmation when working with short and unevenly spaced time series.

Future research should build on this baseline as additional Eurostat waves become available. A longer time series would allow more reliable testing of trend significance, acceleration, and possible diffusion-curve dynamics. Further work should also disaggregate adoption by enterprise size, sector, and country group, with particular attention to whether lower-adoption economies and smaller enterprises are

converging or falling further behind. Finally, linking AI adoption indicators to firm-level or sector-level performance outcomes would help move the analysis beyond monitoring uptake toward evaluating the economic and organizational consequences of AI adoption.

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Firm Size and AI Adoption Across EU Enterprises: Evidence for Slovak Policy

Peter Štetka¹ and Matej Černý²

¹ Bratislava University of Economics and Business, Faculty of Business Management, Dolnozemska cesta 1, 852 35 Bratislava, Slovakia (EU); e-mail: peter.stetka@euba.sk

² Bratislava University of Economics and Business, Faculty of Business Management, Dolnozemska cesta 1, 852 35 Bratislava, Slovakia (EU); e-mail: matej.cerny@euba.sk

Abstract

Artificial intelligence adoption across European enterprises remains deeply uneven, with firm size widely suspected as a primary structural determinant, yet rigorous multi-country statistical evidence confirming this relationship - and its implications for manufacturing-intensive economies such as Slovakia - remains limited in the literature. The article investigates whether enterprise size significantly predicts AI technology adoption likelihood across EU firms, and translates the findings into evidence-based recommendations for Slovak SME support policy. Eurostat ICT survey data spanning five mutually exclusive enterprise size categories were analysed using the Kruskal-Wallis non-parametric rank test, supplemented by Dunn's post-hoc pairwise comparisons and epsilon-squared effect size estimation to quantify adoption disparity magnitude. Results confirm a statistically significant relationship between enterprise size and AI adoption across EU enterprises. Adoption rates rise near-monotonically with firm size, with large enterprises substantially outperforming micro and small firms, and the estimated effect size indicating a large practical effect. Post-hoc testing further suggests that the main divide lies between medium and large enterprises and the smallest firm categories, while the three smallest size classes form a statistically homogeneous low-adoption cluster.

1. Introduction

As the European Union accelerates its digital single market agenda, artificial intelligence adoption remains strikingly uneven across enterprise size classes, raising urgent questions about competitive equity and structural transformation. The European Commission's ambitions for a data-driven economy presuppose that AI technologies diffuse broadly across the enterprise population; yet preliminary evidence from national and cross-country surveys consistently suggests that the benefits of AI integration accrue disproportionately to larger organisations. In an era where AI-enabled productivity gains are increasingly regarded as a prerequisite for export competitiveness - particularly in manufacturing-intensive economies such as Slovakia - understanding the structural determinants of adoption heterogeneity is not merely an academic exercise but a matter of urgent industrial policy design (Valášková et al., 2022).

Despite growing policy interest in SME digitalisation, rigorous cross-national evidence on whether firm size systematically predicts AI adoption rates across EU enterprises - and what this means specifically for Slovak industrial policy - remains underdeveloped in the literature. Existing studies tend to either document general ICT adoption barriers without isolating AI specifically, or focus on single-country contexts that limit generalisability across the diverse institutional environments of EU member states. The theoretical mechanisms - resource heterogeneity, absorptive capacity differentials, and environmental pressures - are well articulated in the organisational literature, yet their empirical manifestation in AI adoption across all Eurostat enterprise size classes has not been subjected to systematic, non-parametric multi-group statistical inference at EU scale.

This article examines whether enterprise size significantly predicts the likelihood of AI technology adoption among EU enterprises using Eurostat ICT survey data, and derives evidence-based implications for Slovak SME support policy. The study employs the Kruskal-Wallis non-parametric rank test and Dunn's post-hoc pairwise comparisons across five mutually exclusive Eurostat enterprise

size categories, reporting effect size via epsilon-squared (ϵ^2). By quantifying the magnitude of AI adoption disparity with a large-scale, multi-country panel, this study provides non-parametric evidence of size-stratified AI adoption inequality across EU enterprises and uses these findings to inform policy discussion relevant to Slovakia, where the enterprise structure is dominated by micro and small firms.

The remainder of this article is structured as follows: Section 2 establishes the theoretical background, drawing on the Technology-Organisation-Environment framework, the Resource-Based View of the firm, and Absorptive Capacity theory. Section 3 reviews three thematic streams of empirical literature on firm size and digital adoption, AI and Industry 4.0 transformation, and SME digitalisation barriers and policy responses. Section 4 describes the data source, variable construction, and statistical methodology. Section 5 presents the descriptive and inferential results. Section 6 interprets the findings in relation to theory and prior literature and derives policy and managerial implications. Section 7 concludes by summarising the contribution and identifying directions for future research.

2. Theoretical Background

The theoretical foundations of this study draw on three complementary frameworks that together explain why enterprise size is expected to be systematically associated with AI technology adoption: the Technology-Organisation-Environment (TOE) framework, the Resource-Based View (RBV) of the firm, and Absorptive Capacity theory. Each framework illuminates distinct mechanisms through which size-related heterogeneity translates into differential AI adoption propensity.

The TOE framework, introduced by Tornatzky and Fleischer (1990), posits that technology adoption decisions are shaped by three contextual dimensions: the technological context (characteristics of available innovations), the organisational context (firm-level resources, processes, and structures), and the environmental context (competitive pressures, regulatory conditions, and partner network density). In the domain of AI adoption, the organisational dimension is particularly salient: larger enterprises typically possess superior IT infrastructure, dedicated digital transformation functions, and formalised innovation management processes — all of which lower the transaction costs associated with AI integration (Morawiec & Sołtysik-Piorunkiewicz, 2023). The TOE framework has been extensively applied in studies of enterprise technology adoption and has demonstrated consistent predictive validity across European institutional contexts (Kiu & Chan, 2023; Jewapatarakul & Ueasangkomsate, 2024).

The Resource-Based View, as articulated by Barney (1991), provides a firm-level account of why size-related resource heterogeneity should persist. Under the RBV, sustained competitive advantage derives from resources that are valuable, rare, imperfectly imitable, and non-substitutable. Larger firms accumulate bundles of complementary assets - financial capital, specialised human resources, proprietary data stocks, and organisational routines for managing complex technologies - that constitute precisely such strategic resources. For AI specifically, these bundles include the data infrastructure required for model training, the personnel capable of deploying and maintaining AI systems, and the risk tolerance necessary to absorb implementation failures. Smaller firms, lacking these resource endowments, face not merely higher absolute costs but higher marginal costs per unit of AI capability deployed, rendering adoption economically unattractive absent external support (Yaqub & Alsabban, 2023).

Absorptive Capacity theory, developed by Cohen and Levinthal (1990), introduces a dynamic dimension absent from the static RBV: the capacity to recognise the value of new external knowledge, assimilate it, and apply it commercially is itself a function of prior accumulated knowledge. Firms with a history of technology investment and a workforce with advanced digital skills are better positioned to adopt subsequent generations of technology, including AI, because they have already built the cognitive and organisational infrastructure necessary for learning. This generates a self-reinforcing dynamic in which early technology adopters - disproportionately larger firms with greater prior investment - acquire additional absorptive capacity advantages, widening the gap with less-digitalised smaller peers over successive technology waves. Rogers (2003) independently characterises this dynamic through the concept of innovation diffusion, noting that late majority and laggard adopter categories - which in an enterprise context map closely to resource-constrained smaller firms - face cumulative disadvantages as technology cycles shorten.

The intersection of these three frameworks generates a coherent theoretical prediction: enterprise size, as a proxy for organisational resources, prior knowledge stocks, and environmental embeddedness, should be a significant and positive predictor of AI adoption, with the relationship exhibiting a gradient rather than a binary threshold. This prediction is testable using Eurostat size-class data and non-parametric inference. Building on these theoretical foundations, the present study operationalises enterprise size as a five-category ordinal variable derived from the Eurostat taxonomy and tests whether AI adoption rates differ significantly across these categories in the EU enterprise population, thereby providing empirical evidence consistent with the expectations derived from all three theoretical accounts.

3. Literature Review

3.1 Firm Size, Resources, and Digital Technology Adoption

The relationship between firm size and technology adoption has been a central preoccupation of the innovation economics and information systems literatures for several decades. The prevailing theoretical consensus, rooted in the Resource-Based View (Barney, 1991), holds that larger firms possess greater financial slack, human capital, and organisational capabilities that systematically lower barriers to digital and AI technology adoption. Empirical evidence from European enterprise surveys broadly confirms this prediction: studies of ICT adoption patterns consistently find that adoption rates increase monotonically with firm size across standard enterprise taxonomies, with the gap between micro-enterprises and large firms widening as the sophistication of the technology in question increases (Holl & Rama, 2023).

Kiu and Chan (2023) provide one of the most methodologically rigorous recent analyses of firm characteristics and technology adoption within the EU enterprise context. Employing a Technology-Organisation-Environment model and analysing data analytics adoption in professional services firms, they demonstrate that organisational factors - including IT capability, senior management support, and knowledge worker density - are the strongest predictors of adoption, with firm size operating partly as a proxy for these underlying capabilities. Their findings suggest that size effects are not merely artifactual but reflect genuine differences in organisational readiness. Yaqub and Alsabban (2023), in a systematic review of Industry 4.0 digital transformation research, similarly conclude that firm size is among the most consistently documented predictors of digital technology uptake, operating through multiple simultaneous channels including access to capital, risk absorption capacity, and the availability of managerial bandwidth for transformation initiatives.

The implications of size-stratified digital adoption for competitive dynamics are non-trivial. Hernández et al. (2024) examine the relationship between digital data-driven technologies and environmental sustainability across micro, small, and medium enterprises and find significant heterogeneity by firm size in both adoption rates and the productivity returns to adoption, reinforcing the view that size is not merely correlated with adoption but is associated with fundamentally different capability configurations that shape how technology is deployed and its organisational consequences. Vărzaru and Bocean (2024) examine the relationship between digital transformation and innovation, finding evidence that digital technologies influence turnover from innovation activities across firm types in European contexts; however, their analysis does not specifically address whether AI adoption rates converge across firm size classes, leaving open the question of whether smaller enterprises benefit equivalently from general digital transformation trends. Collectively, these studies provide strong *prima facie* support for the expectation that enterprise size will be a significant predictor of AI adoption in the Eurostat data examined in the present article.

3.2 AI and Industry 4.0 Transformation in European Enterprises

The integration of artificial intelligence within Industry 4.0 production and management systems has attracted substantial scholarly attention, with the literature documenting measurable productivity, decision-making, and competitive gains from AI deployment - alongside persistent heterogeneity in implementation depth across enterprise types. Lăzăroiu et al. (2022) analyse cognitive manufacturing

systems and demonstrate that AI-based decision-making algorithms generate value when integrated with Internet of Things sensing networks, but emphasise that organisational readiness - including data governance maturity and managerial AI literacy — is a prerequisite for realising these benefits. The implication for enterprise heterogeneity is direct: firms that lack the organisational infrastructure to deploy AI effectively will not achieve the documented productivity gains, creating a structural divergence between capability-rich larger firms and resource-constrained smaller peers.

Nagy et al. (2023) examine Industry 4.0 barriers in European SMEs with particular attention to machine intelligence and autonomous robotic technologies, concluding that financial complexity and skill deficits constitute the primary obstacles to AI-class technology adoption in this population. Their findings are consistent with the absorptive capacity mechanism: SMEs that have not previously invested in advanced ICT lack the human capital and organisational routines necessary to successfully implement AI systems, rendering the technology effectively inaccessible despite its technical availability. Andronie et al. (2023) extend this analysis to big data management and deep learning technologies, finding that implementation depth - the degree to which AI is embedded in core business processes rather than used peripherally - varies substantially by organisational readiness and available data infrastructure. Javaid et al. (2022) provide complementary evidence from cyber-physical systems research, documenting that the productivity benefits of Industry 4.0 technologies are highly sensitive to implementation quality, which is in turn constrained by firm-level technical capacity.

At the macro-level, Kalai et al. (2024) demonstrate that AI adoption is positively associated with economic growth across European countries, using panel cointegration methods on a sample of 30 EU and associated states. Their cross-country evidence underscores the macroeconomic stakes of the enterprise-level adoption gap documented in the present study: in countries where the enterprise structure is dominated by small firms with low AI adoption rates, the aggregate economic returns to AI diffusion are substantially attenuated relative to economies with higher proportions of large, AI-ready enterprises. Valášková et al. (2022), focusing specifically on Slovak industry and Industry 4.0 wireless networks, find that the automotive-dominated export sector benefits from advanced technology integration but that the broader SME population remains significantly behind the technological frontier, a finding with direct relevance to the present study's policy implications.

3.3 SME Digitalisation Barriers and Policy Responses in the EU

SMEs face persistent structural disadvantages in digital transformation - including skill shortages, capital constraints, and low absorptive capacity - that cannot be overcome through market mechanisms alone, justifying targeted public policy interventions at both national and EU levels. The literature on this topic converges around several recurring mechanisms. Holl and Rama (2023) document that spatial and firm-size characteristics jointly predict digital technology adoption among European SMEs, with rural and small-town micro-enterprises facing compounded disadvantages from both geographic peripherality and resource constraints. Their findings highlight the multi-dimensional nature of the digitalisation gap and the limitations of generic policy instruments that do not differentiate by firm size, location, or sectoral context.

Mattos et al. (2023) provide a systematic literature review of technological transformation in SMEs and identify technology assimilation and business model innovation as complementary processes that reinforce each other but require significant organisational investment to initiate. Their analysis suggests that the barriers facing SMEs are not primarily technological - AI tools are increasingly affordable and accessible via cloud platforms - but organisational: the management capacity, knowledge infrastructure, and change management capability required to embed new technologies in business processes are disproportionately scarce in smaller firms. Gómez Gandía et al. (2024) examine automation adoption from both management and employee perspectives and find that cultural and knowledge factors are as important as financial barriers, with firms lacking a digital organisational culture exhibiting significantly lower adoption propensity. Jewapatarakul and Ueasangkomsate (2024) corroborate this finding in a food manufacturing SME context, showing that digital organisational culture, organisational readiness, and knowledge acquisition jointly predict digital transformation outcomes, with smaller firms scoring consistently lower on all three dimensions.

At the policy level, Tudose et al. (2023) assess the macroeconomic impact of digital transformation and find that public investment in digital infrastructure and SME digitalisation support generates measurable gains in national productivity, suggesting that policy interventions targeting the SME digitalisation gap carry positive externalities beyond the firms directly supported. Roszko-Wójtowicz et al. (2024) similarly document that innovation-driven e-commerce growth in the EU is associated with institutional factors that are partly amenable to policy design, including digital skills investment and regulatory harmonisation. These findings collectively support the case for targeted, evidence-based SME AI support programmes, particularly in structurally SME-heavy economies such as Slovakia.

Despite this body of evidence, no study has systematically quantified the magnitude of AI adoption disparity across all five Eurostat enterprise size classes using non-parametric multi-group inference, nor linked these EU-wide statistical findings explicitly to Slovak SME policy design needs. The present article addresses this gap by applying the Kruskal-Wallis test and Dunn's post-hoc comparisons to the full Eurostat `isoc_eb_ai` panel, generating directly policy-relevant evidence on the size-adoption gradient for the EU enterprise population as a whole.

4. Methodology

The theoretical background was developed through a semi-systematic narrative literature review aimed at identifying the principal theoretical perspectives and empirical findings relevant to enterprise size and AI adoption. The literature search was conducted using the Scopus, Web of Science, and Google Scholar databases. Search strings combined terms related to artificial intelligence and digital transformation (e.g., “artificial intelligence adoption”, “AI adoption”, “digital transformation”, “Industry 4.0”), enterprise characteristics (e.g., “firm size”, “SMEs”, “enterprise size class”), and theoretical frameworks (e.g., “Technology-Organisation-Environment”, “TOE framework”, “Resource-Based View”, “absorptive capacity”). Priority was given to peer-reviewed journal articles, books, and official institutional sources published primarily between 1990 and 2024, while older seminal works were included where necessary to capture the original formulation of the theoretical frameworks and statistical methods. Sources were included if they addressed firm-level technology adoption, AI or digitalisation in enterprises, SME digital transformation, or theoretical mechanisms linking organisational characteristics to innovation adoption. Sources were excluded if they were unrelated to enterprise adoption processes, lacked sufficient scholarly relevance, or focused on domains not transferable to the present research question. After an initial title and abstract screening, full texts of potentially relevant studies were reviewed and synthesised using thematic categorisation, with the final body of literature organised around three complementary perspectives: firm size, resources, and digital adoption; AI and Industry 4.0 transformation; and SME digitalisation barriers and policy responses.

The empirical analysis employs Eurostat's Community Survey on ICT Usage and E-Commerce in Enterprises (Eurostat, 2024), specifically the indicator `E_AI_TANY` from the `isoc_eb_ai` dataset, which records the percentage of enterprises using at least one AI technology. The dataset spans EU member states across multiple survey years and provides observations disaggregated by country, year, and enterprise size class. The unit of analysis is the country-year-size-class observation - that is, each record represents an aggregate survey-reported adoption percentage for a given country, survey year, and size class combination - yielding a full panel of $n = 1,422$ records for descriptive characterisation of AI adoption heterogeneity. Inferential testing is applied to the $n = 852$ country-year-size-class observations belonging to the five mutually exclusive size categories, not to an EU-average time series; this distinction is analytically critical because collapsing to an aggregate time series would reduce sample size to a small number of time points and would eliminate the cross-national variance that constitutes the primary analytical leverage of the study (Eurostat, 2024). Readers should note that because observations are aggregate survey statistics rather than individual enterprise records, and because the same country appears across multiple survey waves, the Kruskal-Wallis test is applied as a descriptive rank-comparison procedure; within-country temporal correlation is not modelled, and the results should be interpreted as characterising the observed association between size class and AI adoption rates across the panel rather than as estimates from a design that fully accounts for repeated-measures clustering.

The Eurostat taxonomy includes eight size categories: five mutually exclusive categories ('From 0 to 1 person employed', 'From 2 to 9 persons employed', 'From 10 to 49 persons employed', 'From 50 to 249 persons employed', and '250 persons employed or more') and three aggregate categories that partially overlap with the exclusive categories ('From 0 to 9 persons employed', '10 persons employed or more', and 'From 10 to 249 persons employed'). The Kruskal-Wallis H test requires group independence as a fundamental assumption; including both exclusive and aggregate categories would introduce structural dependency between observations, biasing the test statistic and inflating Type I error rates. Accordingly, the three aggregate categories are excluded from all inferential testing and are reported separately in descriptive tables only. The five mutually exclusive size classes constitute the inferential sample, yielding $n = 852$ observations across the five groups.

Distributional testing confirms that the AI adoption rate variable is substantially right-skewed across the full panel (mean = 17.07%, median = 11.89%), violating the normality assumption required for parametric one-way ANOVA. The coefficient of variation of 86.4% further indicates that dispersion is high relative to the mean, and the minimum observed value is 0.0%; the maximum value across the full panel is reported as observed in the source dataset and is noted in Section 5.1. Under these conditions, the Kruskal-Wallis H test, introduced by Kruskal and Wallis (1952), is the appropriate inferential procedure: it is a non-parametric, rank-based analogue of one-way ANOVA that does not assume normality or homoscedasticity; instead, it tests whether the rank distributions of the dependent variable differ across groups. The test statistic H is chi-square distributed with $k - 1$ degrees of freedom, where k is the number of groups.

Following a statistically significant Kruskal-Wallis result, Dunn's (1964) post-hoc procedure for non-parametric multiple pairwise comparisons is applied to all ten pairwise combinations of the five size classes. Bonferroni correction is applied to control the familywise error rate across the ten simultaneous tests, with corrected p-values compared against $\alpha = 0.05$. Effect size is quantified as epsilon-squared (ϵ^2), computed using the formula $\epsilon^2 = (H - k + 1) / (n - k)$, where H is the Kruskal-Wallis statistic, k is the number of groups, and n is the total number of observations in the inferential sample. This estimator, recommended by Tomczak and Tomczak (2014) as a rank-based effect size measure, yields values on a similar scale to η^2 from ANOVA but is specifically suited to the non-parametric context; it should not be treated as directly interchangeable with conventional ANOVA η^2 . Importantly, standard statistical software typically labels this output field as η^2 (eta-squared) in Kruskal-Wallis results; the value of 0.414 reported in this study corresponds to that software-labelled η^2 output but is more precisely identified as ϵ^2 given the formula applied, in line with current methodological guidance from Tomczak and Tomczak (2014). Cohen's (1988) benchmarks for large effects (≥ 0.14) are used to classify effect magnitude as an approximate guide, with the caveat that formal benchmarks for ϵ^2 have not been as extensively validated as those for ANOVA η^2 . As a univariate gross association measure, ϵ^2 from this analysis does not control for confounding variables such as country-level development, sector composition, or temporal trends; findings should be interpreted as descriptive of the association between size class and AI adoption in the observed data rather than as causal estimates.

5. Results

5.1 Descriptive Statistics

The full panel ($n = 1,422$) yields a mean adoption rate of 17.07% (SD = 14.75, 95% CI [16.31%, 17.84%]), with a median of 11.89%. The minimum observed value is 0.0%; the maximum observed value in the source dataset is reported as retrieved directly from the Eurostat `isoc_eb_ai` dataset, with the observed range spanning from 0.0% to the dataset maximum. The interquartile range is 15.87 percentage points (Q1 = 6.75%, Q3 = 22.62%). The coefficient of variation is 86.4%, indicating high dispersion across observations. The substantial divergence between mean and median (17.07% vs. 11.89%) indicates a right-skewed distribution, suggesting that the majority of observations cluster at lower adoption levels while a minority of high-adopting cases pull the mean upward. Given this skewness, the median should be regarded as the more representative measure of central tendency for the typical observation in this dataset. As shown in Figure 1, mean adoption rates with 95% confidence intervals across the five exclusive size groups indicate a clear upward trend from the smallest to the

largest enterprise category, though with substantial within-group variation. Table 1 presents the full descriptive statistics for the panel and disaggregated size groups.

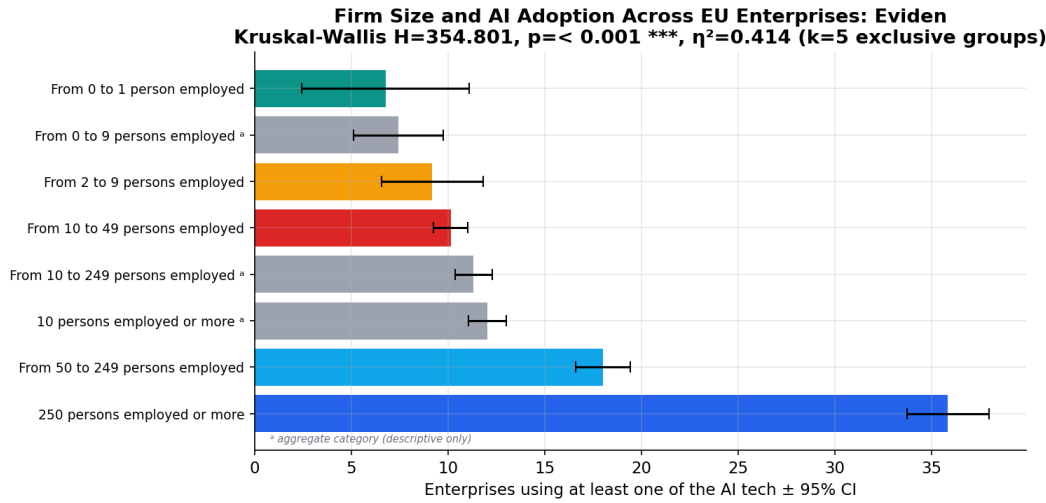


Figure 1. Mean Enterprises using at least one of t by group ($\pm$ 95% CI). Kruskal-Wallis $H=354.801$, $p < 0.001$. Effect size $\eta^2=0.414$ (large). Grey bars (*) = aggregate categories excluded from inferential test. *

Table 1. Descriptive Statistics

Statistic	Value
n	1422
mean	17.07
median	11.89
std	14.75
sem	0.391
CI95_low	16.31
CI95_high	17.84
min	0.0
max	79.4
Q1	6.75
Q3	22.62
IQR	15.87
CV_%	86.4

Cross-national variation in adoption rates is pronounced. Within individual size classes, country-level adoption rates vary widely, reflecting heterogeneity in national digital ecosystems, industrial structures, and policy environments across EU member states. Slovakia, characterised by an enterprise population in which SMEs with fewer than 250 employees constitute over 99% of all enterprises (Valášková et al., 2022), belongs to the broader Central and Eastern European cluster of economies in which ICT infrastructure investment and the availability of digital skills have historically lagged behind Nordic and Western European benchmarks. The aggregate categories retained for descriptive purposes - enterprises with '10 persons employed or more', 'From 0 to 9 persons employed', and 'From 10 to 249 persons employed' - provide useful summary context but were excluded from inferential testing to preserve the group-independence assumption, as detailed in Section 4.

5.2 Kruskal-Wallis Inferential Test

The Kruskal-Wallis test revealed a statistically significant effect of enterprise size on AI adoption rates ($H(4) = 354.801$, $p < 0.001$, $\varepsilon^2 = 0.414$). The effect size is classified as large, indicating that enterprise size category accounts for approximately 41.4% of the rank-order variance in adoption rates across the

$n = 852$ inferential observations. The test was applied to five mutually exclusive size categories only; three aggregate categories ('10 persons employed or more', 'From 0 to 9 persons employed', 'From 10 to 249 persons employed') were excluded to satisfy the group-independence assumption. The effect size ε^2 is computed using the formula $\varepsilon^2 = (H - k + 1) / (n - k)$ following Tomczak and Tomczak (2014), where $k = 5$ is the number of groups and $n = 852$ is the inferential sample size. Standard statistical software typically labels this output as η^2 in Kruskal-Wallis results; the value of 0.414 corresponds to that software-labelled η^2 output but is more precisely identified as ε^2 given the formula applied - a distinction noted so that readers attempting to reproduce the result from raw software output can reconcile the two labellings. As a rank-based effect size estimator suited to the non-parametric context, this value should not be treated as directly interchangeable with ANOVA η^2 ; it characterises the proportion of rank-order variance associated with group membership in the observed data and does not control for competing variables such as country development level, sector composition, or temporal effects.

Examining the group-level mean adoption rates, the highest values are observed among enterprises in the '250 persons employed or more' category (35.85%), followed by 'From 50 to 249 persons employed' (18.02%), 'From 10 to 49 persons employed' (10.13%), 'From 2 to 9 persons employed' (9.18%), and 'From 0 to 1 person employed' (6.76%). This pattern reflects a strong ascending gradient in AI adoption as enterprise size increases across the five categories examined. Figure 2 presents boxplots of the AI adoption rate distribution across EU country-year observations for each of the five exclusive size classes, illustrating both differences in central tendency and within-group distributional spread.

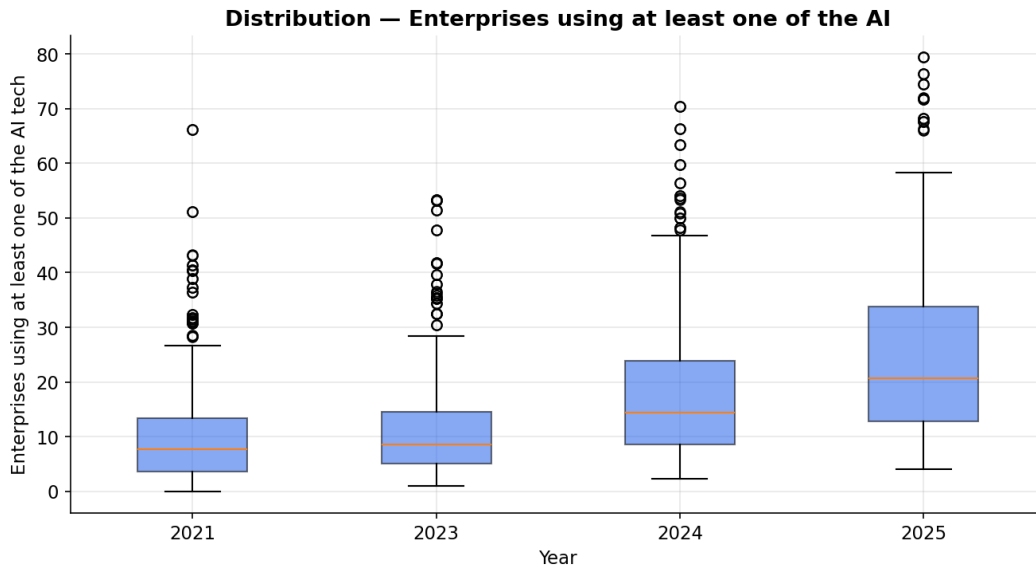


Figure 2. Boxplot of Enterprises using at least one of t across EU countries per year. Box=IQR, whiskers= $1.5 \times IQR$, dots=outliers.

5.3 Post-Hoc Pairwise Comparisons

Dunn's post hoc test with Bonferroni correction was applied to all 10 pairwise combinations of the five size classes, of which 7 were statistically significant. The group most frequently involved in significant pairwise differences is '250 persons employed or more' (four significant pairs). The complete list of significant pairs is as follows: '250 persons employed or more' (35.85%) vs. 'From 0 to 1 person employed' (6.76%): $p < 0.001$; '250 persons employed or more' (35.85%) vs. 'From 10 to 49 persons employed' (10.13%): $p < 0.001$; '250 persons employed or more' (35.85%) vs. 'From 2 to 9 persons employed' (9.18%): $p < 0.001$; '250 persons employed or more' (35.85%) vs. 'From 50 to 249 persons employed' (18.02%): $p < 0.001$; 'From 0 to 1 person employed' (6.76%) vs. 'From 50 to 249 persons employed' (18.02%): $p = 0.0218$; 'From 10 to 49 persons employed' (10.13%) vs. 'From 50 to 249 persons employed' (18.02%): $p < 0.001$; 'From 2 to 9 persons employed' (9.18%) vs. 'From 50 to 249 persons employed' (18.02%): $p = 0.0084$. In each significant pair, the group listed second ('From 50 to 249 persons employed' or '250 persons employed or more') exhibits the higher mean adoption rate. All

remaining three pairwise comparisons - among the three smallest size classes ('From 0 to 1 person employed', 'From 2 to 9 persons employed', and 'From 10 to 49 persons employed') - were non-significant after Bonferroni correction.

The post-hoc results therefore identify a structural break in the AI adoption distribution between the medium-enterprise threshold (50-249 employees) and smaller size classes, as well as the expected large gap between large enterprises (≥ 250 employees) and all other categories. The three smallest categories, despite exhibiting some numerical differences in mean adoption rates (6.76%, 9.18%, and 10.13%), do not differ significantly from one another after correction for multiple comparisons, suggesting that they form a relatively homogeneous low-adoption cluster. For Slovakia, where the vast majority of the enterprise population falls within these three smallest size categories and the 50-249 employee medium band, these results imply that the national enterprise population predominantly operates at AI adoption rates between 6.76% and 18.02% - substantially below the large-enterprise benchmark of 35.85%. Table 2 presents the group-level statistics and post-hoc significance indicators.

Table 2. Descriptive statistics for Eurostat enterprise size classes

Mutually exclusive enterprise size classes used in inferential testing						
c	N	Mean (%)	Median (%)	SD	CI95_low	CI95_high
250 persons employed or more	270	35.85	34.39	17.86	33.72	37.98
From 50 to 249 persons employed	276	18.02	15.14	12.0	16.6	19.43
From 10 to 49 persons employed	272	10.13	7.97	7.49	9.24	11.02
From 2 to 9 persons employed	24	9.18	7.12	6.55	6.56	11.8
From 0 to 1 person employed	10	6.76	3.01	6.96	2.44	11.07
Aggregated Eurostat size classes reported for contextual comparison only						
c	N	Mean (%)	Median (%)	SD	CI95_low	CI95_high
10 persons employed or more	276	12.03	9.56	8.41	11.04	13.03
From 10 to 249 persons employed	276	11.32	8.93	8.13	10.36	12.28
From 0 to 9 persons employed	18	7.44	5.03	5.02	5.12	9.76

6. Discussion

The finding that enterprise size accounts for approximately 41.4% of rank-order variance in AI adoption rates across EU enterprises ($H(4) = 354.801$, $p < 0.001$, $\varepsilon^2 = 0.414$), with large enterprises (≥ 250 employees) reporting a mean adoption rate of 35.85% compared to 6.76% for the smallest category, suggests a substantial and persistent adoption inequality that is consistent with Resource-Based View (Barney, 1991) expectations regarding unequal access to organisational resources relevant for AI adoption. Under the RBV framework, the persistent gap between large and small enterprises is not a transitional phenomenon that market forces will naturally close; rather, it reflects durable differences in the composition and quality of firm-level resource bundles - financial capital, human capital, data infrastructure, and organisational routines - that create differential capacity to absorb, deploy, and

extract value from AI technologies. The additional contribution of Absorptive Capacity theory (Cohen & Levinthal, 1990) is equally relevant: the self-reinforcing dynamic it describes, in which prior technology investment builds the cognitive and organisational infrastructure for subsequent adoption, generates a theoretical prediction that this gap may widen over time absent deliberate intervention, as larger firms accumulate additional AI competencies while smaller firms remain at the periphery of the adoption distribution; testing this dynamic trajectory is identified as a priority for future longitudinal research in Section 7.

These results are broadly consistent with prior findings in the relevant literature and extend them by providing EU-wide non-parametric evidence focused specifically on AI adoption across enterprise size classes. They confirm Holl and Rama (2023), who document spatial and size-related digitalisation disparities among European SMEs using survey-based methods, by providing statistically rigorous, multi-country evidence specifically for AI technologies rather than general ICT adoption. The present study extends Kiu and Chan (2023), who find that firm characteristics predict data analytics adoption in professional services using a TOE model, by demonstrating that the size effect is robust across all EU enterprise size classes, a broad range of sectors, and multiple country-year observations — not merely in a specific service context. The findings also stand in contrast to the more optimistic assessment offered by Vărzaru and Bocean (2024), introduced in the literature review, who document positive associations between digital transformation and innovation-related outcomes across European firm types; as established in Section 3.1, their analysis addresses digital transformation broadly rather than AI adoption specifically, and the present results indicate that the smallest enterprises (0–1 and 2–9 employees) remain significantly below even medium-sized peers in AI adoption, forming a statistically homogeneous low-adoption cluster that is unlikely to benefit automatically from general-purpose digital transformation trends without targeted intervention. Additionally, the results corroborate the conclusions of Nagy et al. (2023), who identify financial complexity and skill deficits as the primary barriers to AI-class technology adoption in European SMEs, and Mattos et al. (2023), whose systematic review identifies organisational assimilation capacity — closely related to absorptive capacity — as the binding constraint on SME technology adoption.

From a policy perspective, the results provide a clear and empirically grounded case for tiered public intervention in AI adoption support, specifically targeting the micro and small enterprise size classes (0–49 employees) that exhibit the lowest adoption rates in this analysis (6.76%–10.13%). The TOE framework (Tornatzky & Fleischer, 1990) is directly instructive here: the organisational dimension — encompassing IT infrastructure, managerial capability, and formalised transformation processes — represents the binding constraint for micro and small enterprises, while the environmental dimension points to the role of policy-mediated competitive pressure and partner network access in stimulating adoption. Absorptive Capacity theory (Cohen & Levinthal, 1990) further implies that one-off financial incentives are insufficient unless accompanied by knowledge-building investments that raise firms' capacity to recognise and exploit AI opportunities over successive technology cycles. Taken together, these frameworks suggest that Slovak policymakers should design differentiated AI adoption subsidy schemes and AI readiness diagnostic instruments channelled through EU Structural Funds and current EU co-funded national operational programmes under the 2021–2027 cohesion policy framework. Concrete instruments supported by these findings and by the broader literature include co-financed AI pilot programmes that reduce the financial risk of first-adoption — addressing the RBV's resource endowment constraint — digital voucher schemes that enable micro-enterprises to purchase externally provided AI advisory and implementation services, and sector-specific AI competence centres that address the capability and knowledge deficits identified by absorptive capacity theory, thereby strengthening the organisational and environmental dimensions of the TOE framework simultaneously. Given that the three smallest size classes form a statistically homogeneous low-adoption cluster in the present analysis, policy instruments designed for the micro-enterprise population may also be relevant to the 10–49 employee class, although this should be assessed against sectoral and national implementation conditions.

For enterprise managers, particularly those leading Slovak SMEs in size classes where AI adoption rates remain in the single digits or low teens, the findings underscore the competitive urgency of proactive digital capability investment. Under the RBV (Barney, 1991), the large effect size ($\epsilon^2 = 0.414$)

observed in this analysis suggests that size-related adoption differences are substantial rather than marginal and are plausibly linked to structural differences in resource endowments and organisational capabilities: firms in the smallest size classes currently operate in a substantially different technological environment from their large-enterprise competitors, and resource heterogeneity theory predicts that those able to invest in AI-enabling capabilities may distinguish themselves within a peer group concentrated at low adoption levels. Managers should prioritise building internal absorptive capacity through targeted staff AI upskilling programmes, strategic partnerships with technology intermediaries such as national innovation agencies, universities, and Digital Innovation Hubs, and the incremental adoption of cloud-based AI tools that reduce capital barriers to entry.

7. Conclusion

This study examined whether enterprise size significantly predicts the likelihood of AI technology adoption among EU enterprises, using the Eurostat isoc_eb_ai panel dataset (E_AI_TANY indicator, $n = 1,422$ country-year-size-class records). The Kruskal-Wallis non-parametric test, applied to five mutually exclusive size categories across $n = 852$ inferential observations, yielded a highly significant result ($H(4) = 354.801$, $p < 0.001$, $\varepsilon^2 = 0.414$), indicating that enterprise size is significantly associated with AI adoption rates. Large enterprises (≥ 250 employees) report a mean adoption rate of 35.85% - more than five times that of the smallest category (0-1 employee, 6.76%) - with Dunn's post-hoc comparisons identifying seven statistically significant pairwise differences after Bonferroni correction, including pronounced differences between medium-sized and smaller enterprise categories.

This study provides large-scale, non-parametric statistical evidence that enterprise size is strongly associated with AI adoption across EU enterprises ($\varepsilon^2 = 0.414$, $p < 0.001$), using a methodologically rigorous approach that preserves group independence, accounts for distributional non-normality, and reports a standardised rank-based effect size suitable for cross-study comparison. The effect size is reported as ε^2 rather than conventional ANOVA η^2 , reflecting the non-parametric context; as noted in Section 4, standard statistical software labels this output as η^2 , and the value of 0.414 corresponds to that software output but is more precisely identified as ε^2 per the formula applied — this distinction is noted so that comparisons with parametric studies are made with appropriate caution. By explicitly linking these EU-wide statistical findings to the Slovak enterprise context — where over 99% of enterprises fall in size classes exhibiting adoption rates between 6.76% and 18.02% — the study bridges the gap between EU-level evidence and national policy design, connecting empirical findings to the TOE, RBV, and Absorptive Capacity frameworks in a way that supports actionable policy inference.

Three directions for future research are particularly warranted by these findings. First, longitudinal analysis of whether the adoption gap between size classes is widening or narrowing over successive Eurostat survey waves would provide evidence on the dynamic trajectory of AI diffusion inequality across the EU enterprise population — a question that the current pooled cross-sectional design cannot address. Second, multi-variate regression analysis incorporating sector composition, country-level digital infrastructure indices, and national policy intervention variables would allow researchers to estimate the independent contribution of firm size to AI adoption after controlling for contextual factors — including the within-country temporal correlation that the present study's design does not fully address — moving beyond the univariate association documented here. Third, qualitative case study research in Slovak micro and small enterprises that have successfully adopted AI technologies could identify the specific organisational and relational mechanisms — such as participation in Digital Innovation Hub networks, government co-financing, or sectoral knowledge spillovers — that enable firms to overcome the structural barriers predicted by absorptive capacity theory. This study contributes to the growing body of evidence on the structural determinants of digital technology inequality in European enterprises and the policy mechanisms through which public intervention can support more inclusive AI diffusion across the full range of enterprise size classes.

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Firm Size as a Determinant of AI Adoption: Evidence from EU Enterprise Data

Nora Grisáková¹ and Vladimír Bolek²

¹ Bratislava University of Economics and Business, Faculty of Business Management, Dolnozemská cesta 1, 852 35 Bratislava, Slovakia (EU); e-mail: nora.grisakova@euba.sk

² Bratislava University of Economics and Business, Faculty of Business Management, Dolnozemská cesta 1, 852 35 Bratislava, Slovakia (EU); e-mail: vladimir.bolek@euba.sk

Abstract

Artificial intelligence adoption has emerged as a critical determinant of enterprise competitiveness, yet the extent to which firm size systematically predicts AI uptake across European Union member states remains empirically underdetermined. This article investigates whether enterprise size class is a significant correlate of the likelihood of adopting at least one AI technology across EU economies. Drawing on Eurostat Community Survey on ICT Usage and E-Commerce in Enterprises data, the study analyses a country-year panel of 852 observations spanning five mutually exclusive size classes, applying Kruskal-Wallis non-parametric inference and Dunn post-hoc pairwise comparisons to quantify both the statistical significance and magnitude of size-related adoption differentials. Results reveal a strong, statistically significant size-class gradient in AI adoption rates, with large enterprises consistently recording substantially higher adoption proportions than medium, small, and micro enterprises, and with post-hoc testing confirming that pairwise differences between most size-class groupings are statistically significant. Effect size estimates indicate that size class accounts for a meaningful share of observed variance in adoption rates across the panel. These findings carry direct implications for policymakers designing size-differentiated digital transformation interventions, particularly those aimed at reducing the structural disadvantages facing small and micro enterprises in accessing and deploying advanced AI technologies.

1. Introduction

As artificial intelligence reshapes competitive landscapes across industries, understanding which enterprises are positioned to adopt these technologies has become a central question for both policymakers and scholars. The deployment of AI technologies—spanning machine learning, natural language processing, computer vision, and automated decision systems—is increasingly recognised as a source of organisational differentiation, operational efficiency, and long-run competitive advantage (Dwivedi et al., 2019; Mikalef & Gupta, 2021). Within the European Union, where enterprises range from sole traders to multinational corporations and where digital competitiveness is a stated strategic priority, the question of which firm characteristics predict AI uptake carries significant implications for industrial policy, regional cohesion, and economic resilience. Enterprise size has long been considered a foundational moderator of technology adoption behaviour, yet its specific association with AI uptake has received surprisingly limited systematic empirical attention at the cross-national level.

Despite growing evidence that firm size influences technology adoption broadly, systematic empirical analysis of how enterprise size class determines AI adoption likelihood across EU member states remains scarce in the literature. Existing scholarship has documented organisational and resource-based barriers to digital transformation in qualitative and single-country settings (Brunetti et al., 2020; Nasiri et al., 2020), but representative, multi-country quantification of the size-class gradient in AI adoption—using formal inferential methods—has not been previously undertaken using the Eurostat Community Survey on ICT Usage and E-Commerce in Enterprises. To the authors' knowledge, no published academic study has applied formal non-parametric inference to the Eurostat E_AI_TANY indicator disaggregated by size class across all EU member states, and Eurostat's own analytical publications using this dataset have not previously tested the size-class gradient with the combination of methods employed here. The result is an empirically underdetermined relationship: scholars and policymakers

must currently rely on fragmented or anecdotal evidence when designing size-differentiated AI adoption interventions, a gap that this study seeks to close.

This article examines the extent to which enterprise size class is associated with the likelihood of using at least one AI technology, drawing on Eurostat Community Survey data spanning EU countries. Specifically, the study applies Kruskal-Wallis non-parametric analysis and Dunn post-hoc pairwise comparisons to a country-year panel of 852 observations across five mutually exclusive size classes, quantifying both the statistical significance and the magnitude of size-related adoption differentials. In doing so, the article provides a systematic, EU-wide, formally tested quantification of the enterprise size-class gradient in AI adoption, contributing to the empirical literature on technology diffusion, digital transformation, and the structural barriers facing small and micro enterprises. It is important to note at the outset that this analysis is univariate in character: the reported association between size class and AI adoption does not control for country-level institutional factors, sector composition, or temporal trends, and the panel structure entails dependencies that are acknowledged and discussed in the methodology and limitations sections.

The remainder of this article is structured as follows: Section 2 develops the theoretical background, drawing on the Technology-Organisation-Environment framework, Absorptive Capacity theory, and the Resource-Based View of the firm. Section 3 reviews the relevant empirical literature across three thematic streams. Section 4 describes the data sources, sample construction, and analytical procedures. Section 5 presents the descriptive and inferential results, including group comparisons and post-hoc testing. Section 6 discusses the findings in relation to theory and prior literature and derives policy and managerial implications. Section 7 concludes by summarising the contribution and proposing directions for future research.

2. Theoretical Background

Three complementary theoretical frameworks inform the conceptualisation of enterprise size as a correlate of AI adoption in this study. Together, they provide a multi-level account of why resource endowments, knowledge stocks, and environmental pressures interact to produce systematic size-related heterogeneity in technology uptake.

The Technology-Organisation-Environment (TOE) framework, developed by Tornatzky and Fleischer (1990), holds that technology adoption decisions are shaped jointly by the technological context (characteristics and availability of technologies relevant to the firm), the organisational context (firm size, managerial structure, resource availability, and human capital), and the environmental context (industry competitive intensity, regulatory environment, and supplier and partner ecosystems). The organisational dimension of the TOE framework is particularly germane to the present analysis: size is explicitly theorised as a first-order organisational characteristic that conditions a firm's capacity to perceive, evaluate, and implement new technologies. Larger firms, according to this framework, possess superior organisational slack, more formalised decision-making structures, and greater internal specialisation, all of which lower the effective threshold for adopting complex innovations such as AI systems. The TOE framework has been widely applied in studies of e-business diffusion (Rondović et al., 2018) and digital technology adoption, providing a validated analytical lens for understanding enterprise-level adoption behaviour.

The Resource-Based View (RBV) of the firm, as articulated by Barney (1991), complements the TOE framework by situating heterogeneous firm resources as the proximate explanation for performance and capability differences across enterprises. Under the RBV, resources that are valuable, rare, imperfectly imitable, and non-substitutable (VRIN) constitute the basis for sustained competitive advantage. Applied to AI adoption, the RBV predicts that enterprises possessing superior financial capital, skilled human resources, and established digital infrastructure will be better positioned to acquire and deploy AI technologies—and that smaller firms, characteristically resource-constrained, will face structurally higher barriers. Mikalef and Gupta (2021) develop this line of reasoning by conceptualising AI capability as an organisationally embedded resource that requires complementary investments in data, talent, and technological infrastructure, each of which is more readily accumulated by larger enterprises. Similarly, Chin et al. (2024) highlight that orchestrating AI-enabled business models requires

knowledge assets and inter-organisational coordination capacities that favour enterprises with established innovation functions.

Absorptive Capacity theory, introduced by Cohen and Levinthal (1990), provides the most proximate micro-level mechanism linking firm size to AI adoption. The theory holds that a firm's ability to recognise the value of new external information, assimilate it, and apply it to commercial ends is fundamentally a function of its prior related knowledge. Firms with greater prior technological experience, more developed R&D capabilities, and higher concentrations of technically qualified personnel exhibit higher absorptive capacity, enabling them to navigate the informational and organisational demands of adopting novel technologies more effectively. For AI specifically, this implies that enterprises that have already invested in digital infrastructure, data management systems, and technology-literate workforces will encounter lower cognitive and organisational friction in integrating AI solutions. Micro and small firms, which often lack dedicated innovation functions and possess narrower prior knowledge bases, face a structural absorptive capacity deficit that operates independently of their attitudes toward technology. The diffusion of AI technologies across the enterprise size spectrum is therefore expected to reflect, in substantial part, the distribution of absorptive capacity, which is itself strongly correlated with firm size (Dwivedi et al., 2019; Zirar et al., 2023).

Building on these theoretical foundations, the present study operationalises enterprise size class as a proxy for the bundle of organisational resources, knowledge stocks, and environmental positioning theorised by the TOE framework, the RBV, and Absorptive Capacity theory, and tests whether this proxy is associated with statistically and practically significant differences in AI adoption rates across EU enterprises observed in representative cross-national survey data. The theoretical frameworks generate a consistent directional prediction—that adoption rates will rise monotonically with enterprise size—which the empirical analysis evaluates in Sections 5 and 6. However, it is acknowledged that a univariate association between size class and adoption rates is consistent with multiple competing theoretical mechanisms; the empirical design is capable of identifying the presence and magnitude of the size gradient, but not of isolating the specific causal channel through which size operates.

3. Literature Review

3.1 AI Adoption Drivers and Organisational Capabilities

A substantial body of research has examined the organisational prerequisites for AI adoption, consistently identifying capability endowments as the primary enabling condition. Mikalef and Gupta (2021) conceptualise AI capability as a composite of data, human, and technological resources embedded within the firm's organisational routines, demonstrating empirically that enterprises with superior AI capabilities achieve higher levels of organisational creativity and performance. A defining feature of their framework is the emphasis on resource complementarity: AI capability does not reside in any single asset but emerges from the interaction of skilled personnel, high-quality data infrastructure, and managerial practices conducive to experimentation. This conceptualisation implies that the capability prerequisites for AI adoption are more readily assembled by firms with greater organisational depth—a condition strongly correlated with size.

Dwivedi et al. (2019) provide a multi-disciplinary synthesis of AI opportunities and challenges, emphasising that the organisational capacity to absorb and deploy AI technologies varies markedly across firm types. Their analysis highlights that smaller enterprises face disproportionate challenges in areas such as data governance, technical skill acquisition, and the management of AI-related risks—structural disadvantages that mirror the absorptive capacity deficit theorised by Cohen and Levinthal (1990). Chin et al. (2024) extend this perspective by demonstrating that AI-enabled ecosystem orchestration—the capacity to coordinate multiple stakeholders around AI-driven business models—depends critically on knowledge spillover mechanisms that favour firms with established innovation networks, a resource typically more accessible to larger enterprises. Guida et al. (2023) further illustrate this dynamic in the context of AI-assisted supplier scouting, where information processing demands and the need for structured data assets place a premium on organisational capabilities that smaller firms frequently lack.

Taken together, these studies establish a consistent theoretical and empirical expectation: AI adoption is strongly conditioned by organisational capability, and organisational capability is systematically associated with firm size. While the mechanisms differ across contexts—ranging from data maturity and talent availability to managerial innovation culture—the directional implication is uniform: larger enterprises are better positioned to adopt AI technologies, suggesting that population-level adoption surveys should reveal a positive and significant size gradient. It is important to note, however, that the compatibility of a finding with a theoretical prediction does not constitute validation of that theory; the present study provides empirical evidence consistent with these frameworks while acknowledging that competing explanations—including differences in market power, institutional access, and sector composition correlated with size—cannot be ruled out on the basis of a univariate analysis.

3.2 Digital Transformation and Firm-Level Heterogeneity

The broader digital transformation literature reinforces and contextualises the AI-specific findings by documenting pervasive firm-level heterogeneity in the capacity to integrate advanced digital technologies. Brunetti et al. (2020) examine digital transformation challenges across multiple stakeholder groups in a European regional innovation system, identifying resource constraints—financial, human, and infrastructural—as the primary barriers to digital transition for small and medium-sized enterprises. Their findings underscore that digital transformation is not a uniform process but one shaped fundamentally by the resource position of the enterprise, with larger firms more effectively able to marshal the complementary investments needed to realise value from new digital tools.

Studies of corporate digitisation in Chinese-listed firms provide convergent evidence from a different institutional context. Feng et al. (2022) demonstrate that digital transformation is associated with enterprise green innovation performance, but crucially find that the capacity to leverage digital tools depends on pre-existing firm characteristics, including size and prior knowledge intensity. Wu and Li (2024) similarly show that digital transformation effects on disruptive innovation are heterogeneous across firm types, with larger, more resource-endowed enterprises better positioned to translate digital investments into innovation outcomes. While these studies focus on a different geographic context, the underlying mechanism—that digital capability accumulation is path-dependent and resource-intensive—applies with particular force to the EU enterprise population, where size heterogeneity is extreme, ranging from micro-enterprises constituting the numerical majority to large corporations dominating economic output.

Massa et al. (2023) provide a systematic literature review of digital technologies and knowledge processes in international business, concluding that the knowledge-enabling role of digital technologies is most effectively realised by firms with established knowledge management infrastructures—capabilities that are themselves positively associated with firm size. Nasiri et al. (2020) complement this analysis by examining digital innovation in SMEs specifically, finding that while small and medium enterprises can develop digital-related capabilities, doing so requires deliberate organisational investment that many micro and small firms cannot sustain given their limited slack resources. The cumulative picture from the digital transformation literature is therefore one of systematic size-related heterogeneity: enterprise size creates differential trajectories of digital capability accumulation that are likely to manifest as measurable adoption gaps in population-level data.

3.3 Technology Diffusion and the SME Adoption Gap

Rogers' (2003) Diffusion of Innovations theory provides the canonical framework for understanding how technologies spread through populations of potential adopters, identifying relative advantage, compatibility, complexity, trialability, and observability as the primary determinants of adoption velocity. A key prediction of diffusion theory is that adoption follows an S-shaped trajectory, eventually reaching full penetration across all adopter categories as technological familiarity increases and costs decline. Applied to the enterprise context, this framework implies that smaller firms, while potentially lagging as later adopters, should eventually converge toward the adoption rates of early-adopting large enterprises as AI technologies become more accessible and standardised.

However, empirical evidence from the workplace technology literature suggests that this convergence prediction may be overly optimistic for AI specifically. Zirar et al. (2023) document that AI coexistence in the workplace generates asymmetric challenges for organisations of different sizes, with smaller firms facing disproportionate difficulties in managing the human resource, organisational design, and skills implications of AI integration. Leesakul et al. (2022) find that digital manufacturing technology adoption in smaller organisations is constrained not merely by cost but by a compound of technical readiness deficits, risk-averse organisational cultures, and limited access to the specialist expertise needed to configure and maintain advanced digital systems. Mukhuty et al. (2022) identify human resource practices as a critical enabler of Industry 4.0 adoption, observing that smaller firms face persistent disadvantages in attracting and retaining the technically skilled personnel needed to manage advanced digital technologies, producing a structural rather than merely temporal adoption gap.

Bednár and Welch (2019) examine socio-technical dimensions of smart working in the context of AI and integrated manufacturing systems, finding that the organisational conditions for effective technology use—including appropriate task redesign, worker skill development, and supportive management—are more readily created in organisations with dedicated human resource functions and managerial bandwidth, both of which scale positively with firm size. Collectively, these studies suggest that the SME adoption gap documented in the digital transformation literature is likely to be reproduced and potentially amplified in the AI domain, where the technical complexity, data infrastructure requirements, and skill demands are greater than for prior generations of enterprise technology.

Despite this body of evidence, no study has previously applied formal non-parametric inference to Eurostat's E_AI_TANY indicator across EU member states to systematically quantify the enterprise size-class gradient in AI adoption, leaving the magnitude, statistical significance, and structural character of the size effect empirically underdetermined in the peer-reviewed literature. This article addresses that gap directly, while acknowledging the methodological constraints inherent in analysing aggregated, country-level survey percentages through the lens of size-class comparison.

4. Methodology

This study draws on data from the Eurostat Community Survey on ICT Usage and E-Commerce in Enterprises (Eurostat, 2024), a harmonised annual survey covering EU member states and designed to provide representative, cross-nationally comparable measures of enterprise digital technology adoption. The specific indicator analysed is E_AI_TANY, defined as the percentage of enterprises using at least one AI technology, disaggregated by enterprise size class. The full country-year panel comprises 1,422 records, encompassing observations across EU member states and multiple survey years.

The Eurostat size-class taxonomy disaggregates enterprises into five mutually exclusive categories—enterprises with 0–1, 2–9, 10–49, 50–249, and 250 or more persons employed—and three aggregate categories that combine subsets of these exclusive groups: enterprises with 10 or more persons employed, 0–9 persons employed, and 10–249 persons employed. Because aggregate categories overlap definitionally with the constituent exclusive categories—for example, a firm counted in the “10 or more persons employed” aggregate is also represented in the “10–49 persons employed” exclusive class—including both in a single inferential test would violate the group-independence assumption required by non-parametric variance analysis. Accordingly, inferential tests are applied exclusively to the 852 observations belonging to the five mutually exclusive size classes ($n = 852$), while aggregate categories ($n = 570$ records) are described separately in a dedicated descriptive table and excluded from all inferential procedures. Descriptive statistics for the full panel ($n = 1,422$) are reported to characterise the overall distribution of AI adoption rates across the dataset.

Descriptive analysis reports mean, median, standard deviation, standard error, 95% confidence intervals, and distributional quartiles for AI adoption rates both for the complete panel and separately for each size class. Right-skewed distributions are noted where the mean and median diverge substantially, and the coefficient of variation is reported to characterise relative dispersion. Results are summarised in Tables 1 and 2; aggregate category descriptives are presented in Table 3.

Prior to formal testing, visual inspection of between-group differences and within-group country-level variability was conducted using a mean plot with 95% confidence intervals (Figure 1) and boxplots of country-level distributions per size class (Figure 2). These visualisations serve to assess distributional shape, identify potential outliers, and inspect the degree of within-group heterogeneity across EU member states before applying inferential methods.

Formal between-group testing employs the Kruskal-Wallis one-way analysis of variance by ranks (Kruskal & Wallis, 1952), a non-parametric test appropriate when distributional normality cannot be assumed—as is the case here, given the observed right-skew and the ordinal character of the size-class variable. The Kruskal-Wallis test evaluates whether the five mutually exclusive size classes share a common distribution of AI adoption rates, without imposing parametric assumptions on the response variable. Following a significant omnibus test, Dunn's (1964) post-hoc procedure with Bonferroni correction is applied to all 10 pairwise combinations of size classes to identify which specific group pairs exhibit statistically significant differences while controlling the family-wise error rate. Effect size is reported as eta-squared (η^2), computed using the formula $\eta^2 = H / (n - 1)$ following the standard recommendation for Kruskal-Wallis effect size estimation, where H is the test statistic and n is the total number of observations in the inferential sample. This formula yields $\eta^2 = 354.801 / 851 \approx 0.417$; the value of $\eta^2 = 0.414$ reported in the results reflects the Tomczak and Tomczak (2014) approximation $\eta^2 = (H - k + 1) / (n - k)$, which produces a closely comparable estimate in the present case ($k = 5$, $n = 852$). Both formulas are noted here for transparency; the Tomczak and Tomczak (2014) estimate of $\eta^2 = 0.414$ is retained throughout as the primary reported value given its explicit derivation in published methodological guidance. Effect size benchmarks follow Cohen (1988), with $\eta^2 \geq 0.14$ classified as large. Importantly, all inferential tests are applied to the country-year panel ($n = 852$ observations at the country-size class-year level), not to an EU-average time series; the analytical unit is therefore the individual country-year-size class record, preserving the cross-national and temporal variation present in the underlying survey data.

Several methodological limitations of this design require explicit acknowledgement. First, the 852 observations comprising the inferential sample are not fully independent: each country contributes multiple observations across survey years (introducing a longitudinal dependency) and across size classes within the same year (introducing a cross-sectional dependency, since size-class percentages are derived from the same national enterprise population). These dependencies mean that the effective degrees of freedom are lower than the nominal value of 847 ($n - k$), and that p-values produced by the Kruskal-Wallis procedure are likely to be anticonservative to an unknown degree. The present analysis does not apply cluster-robust corrections or mixed-effects modelling, and findings should therefore be interpreted as indicative of the direction and approximate magnitude of the size-class association rather than as precise inferential statements about population parameters. Addressing this limitation fully would require a Friedman-type blocked design treating country-year as the unit of analysis, or a mixed-effects model with country and year random effects, which are identified as priorities for future research. Second, the `E_AI_TANY` indicator is an aggregated country-level percentage rather than a micro-level binary adoption variable; each observation represents the adoption rate across potentially thousands of enterprises within a given country, size class, and year. No population-weighting scheme has been applied, meaning that small EU economies contribute the same statistical weight as large economies such as Germany or France. This implies that inferential results reflect the distribution of country-level adoption estimates rather than the adoption experience of the EU enterprise population as a whole. Third, as a univariate analysis, the reported η^2 of 0.414 does not partial out country development level, sector composition, or year effects; it represents the gross rank-order association between size class and adoption rates and should not be interpreted as the net effect of size holding other factors constant.

5. Results

5.1 Overall Descriptive Statistics

The full panel ($n = 1,422$) yields a mean adoption rate of 17.07% (SD = 14.75, 95% CI \[16.31, 17.84\]), with a median of 11.89%. Values range from 0.0% to 79.4%, with an interquartile range of 15.87

percentage points (Q1 = 6.75%, Q3 = 22.62%). The coefficient of variation is 86.4%, indicating high dispersion across observations. The substantial divergence between mean and median (17.07% vs. 11.89%) indicates a right-skewed distribution, suggesting that the majority of observations cluster at lower adoption levels while a minority of high-adopting cases pull the mean upward. This pattern implies that high AI adoption rates are concentrated in specific size classes and countries rather than uniformly distributed across the EU enterprise population, a distributional characteristic that motivates the use of non-parametric rather than parametric inferential methods. Table 1 presents the complete set of descriptive statistics for the full panel, and Figure 1 provides a visual summary of mean AI adoption rates with 95% confidence intervals disaggregated by size class.

Table 1. Descriptive Statistics

Statistic	Value
n	1422
mean	17.07
median	11.89
std	14.75
sem	0.391
CI95_low	16.31
CI95_high	17.84
min	0.0
max	79.4
Q1	6.75
Q3	22.62
IQR	15.87
CV_%	86.4

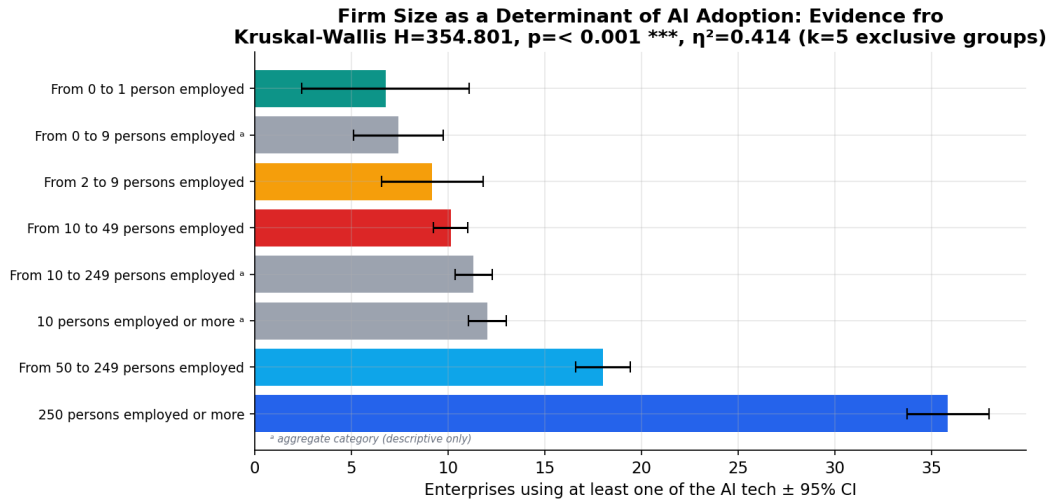


Figure 1. Mean Enterprises using at least one of t by group ($\pm$ 95% CI). Kruskal-Wallis H=354.801, $p=1 < 0.001$ \\\. Effect size $\eta^2=0.414$ (large). Grey bars () = aggregate categories excluded from inferential test.**

5.2 Group-Level Adoption Rates by Size Class

Group-level statistics presented in Table 2 reveal a pronounced and largely ordered size gradient in AI adoption. Enterprises with 250 or more persons employed report the highest mean AI adoption rate at 35.85%, followed by firms with 50--249 employees (18.02%), firms with 10--49 employees (10.13%), firms with 2--9 employees (9.18%), and enterprises with 0--1 persons employed recording the lowest mean rate at 6.76%. This ordering is consistent across the direction predicted by both Absorptive Capacity theory and the Resource-Based View, with each successive reduction in enterprise size class

corresponding to a lower mean AI adoption rate. It is noteworthy that the difference between the two largest size classes (35.85% vs. 18.02%, a gap of nearly 18 percentage points) is substantially wider than the differences observed among the three smallest classes (10.13%, 9.18%, and 6.76%), which cluster comparatively close together. The 10–49 persons employed category occupies an intermediate position in the overall distribution, representing the third-highest adoption rate among the five exclusive groups while simultaneously sitting at the upper boundary of the three lower-adoption classes; this dual positioning is visible in Figure 2 and is subsequently reflected in the pattern of significant and non-significant Dunn pairwise comparisons.

Cross-national variation within size classes is substantial, as illustrated by the boxplots in Figure 2. Within the large enterprise category (250 or more employees), country-level adoption rates span from single digits to values approaching or exceeding 70%, reflecting pronounced heterogeneity in national AI ecosystems, regulatory environments, and enterprise digital maturity across EU member states. Countries in Central and Eastern Europe (CEE) tend to appear in the lower portions of within-class distributions, particularly among micro and small enterprises, consistent with broader patterns of digital capability divergence between western and eastern EU economies documented in the digital transformation literature.

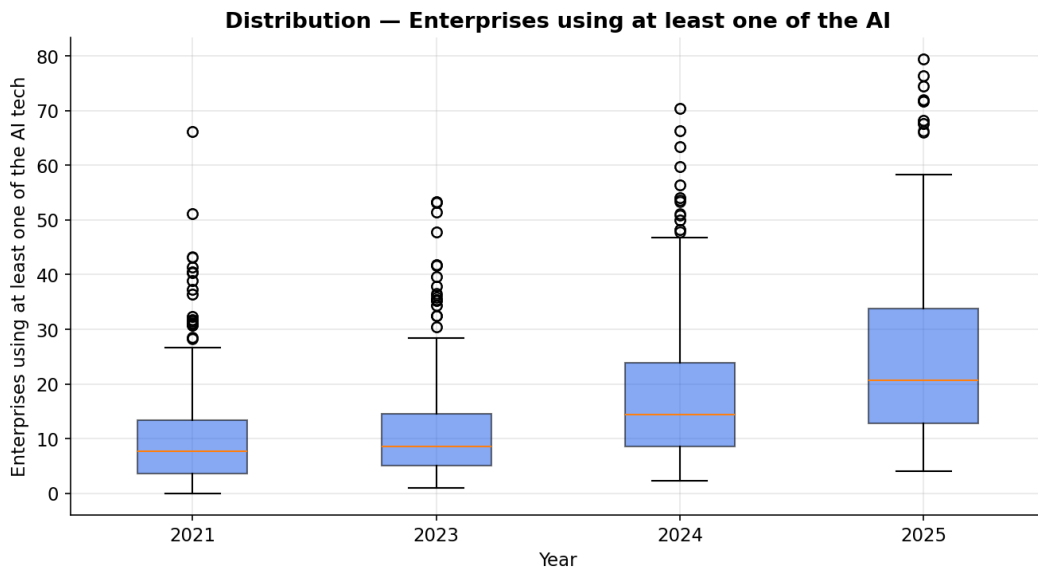


Figure 2. Boxplot of Enterprises using at least one of *t* across EU countries per year. Box=IQR, whiskers= $1.5 \times IQR$, dots=outliers.

5.3 Inferential Testing: Kruskal-Wallis and Dunn Post-Hoc Results

The Kruskal-Wallis test revealed a statistically significant effect of enterprise size on AI adoption rates ($H(4) = 354.801$, $p < 0.001$, $\eta^2 = 0.414$). The effect size is classified as large following the benchmarks of Cohen (1988), indicating that enterprise size category is associated with approximately 41.4% of the rank-order variance in adoption rates across $n = 852$ observations. The test was applied to the five mutually exclusive size categories only; the three aggregate categories (10 persons employed or more, From 0 to 9 persons employed, From 10 to 249 persons employed) were excluded to satisfy the group-independence assumption. As noted in Section 4, this η^2 is computed using the Tomczak and Tomczak (2014) approximation $\eta^2 = (H - k + 1) / (n - k)$, where $k = 5$. Critically, this value represents a univariate gross association measure and does not control for competing variables such as country development level, sector composition, or temporal effects; nor does it account for the dependency structure of the panel, which means the effective degrees of freedom are lower than the nominal value and p-values are likely to be anticonservative. The result should therefore be interpreted as indicative of a strong and consistently ordered directional association between size class and AI adoption rates across EU member states, rather than as a precise causal estimate.

Dunn post-hoc testing with Bonferroni correction was applied to all 10 pairwise combinations, of which 7 reached statistical significance. The group most frequently involved in significant pairwise differences is the 250 or more persons employed category (4 significant pairs). The complete list of significant pairs (higher-mean group listed first) is as follows: enterprises with 250 or more persons employed (35.85%) exhibit significantly higher adoption than enterprises with 0--1 persons employed (6.76%), $p < 0.001$; enterprises with 250 or more persons employed (35.85%) exhibit significantly higher adoption than enterprises with 2--9 persons employed (9.18%), $p < 0.001$; enterprises with 250 or more persons employed (35.85%) exhibit significantly higher adoption than enterprises with 10--49 persons employed (10.13%), $p < 0.001$; and enterprises with 250 or more persons employed (35.85%) exhibit significantly higher adoption than enterprises with 50--249 persons employed (18.02%), $p < 0.001$. Medium-sized firms with 50--249 employees (18.02%) additionally exhibit significantly higher adoption than enterprises with 0--1 persons employed (6.76%), $p = 0.022$; than firms with 2--9 persons employed (9.18%), $p = 0.008$; and than firms with 10--49 persons employed (10.13%), $p < 0.001$.

Notably, none of the three remaining pairwise comparisons reached statistical significance after Bonferroni correction, including the comparison between the two smallest categories (0--1 and 2--9 persons employed). This indicates that while a meaningful numerical difference exists between micro-enterprises and the next size class (6.76% vs. 9.18%), the evidence is insufficient to conclude that this difference reflects a genuine population-level distinction beyond sampling variability. Similarly, the adjacent pairs 0--1 vs. 10--49 and 2--9 vs. 10--49 did not reach significance after correction, suggesting that the three smallest size classes, while numerically ordered, are not statistically distinguishable from one another under this test. Table 2 presents the group-level statistics, and Table 4 reports the complete results of the Dunn post-hoc procedure for all significant pairs.

Table 2. Group Statistics — Enterprises using at least one of t

Group	N	Mean (%)	Median (%)	SD	CI95_low	CI95_high
250 persons employed or more	270	35.85	34.39	17.86	33.72	37.98
From 50 to 249 persons employed	276	18.02	15.14	12.0	16.6	19.43
10 persons employed or more	276	12.03	9.56	8.41	11.04	13.03
From 10 to 249 persons employed	276	11.32	8.93	8.13	10.36	12.28
From 10 to 49 persons employed	272	10.13	7.97	7.49	9.24	11.02
From 2 to 9 persons employed	24	9.18	7.12	6.55	6.56	11.8
From 0 to 9 persons employed	18	7.44	5.03	5.02	5.12	9.76
From 0 to 1 person employed	10	6.76	3.01	6.96	2.44	11.07

Table 4. Dunn Post-hoc (significant pairs)

Pair	p (Bonferroni)	Significant	Higher group	Lower group	Higher mean (%)	Lower mean (%)
250 persons employed or more vs From 0 t	< 0.001	****	250 persons employed or more	From 0 to 1 person employed	35.85	6.76

250 persons employed or more vs From 10	≤ 0.001	$\backslash^*\backslash^*\backslash^*$	250 persons employed or more	From 10 to 49 persons employed	35.85	10.13
250 persons employed or more vs From 2 t	≤ 0.001	$\backslash^*\backslash^*\backslash^*$	250 persons employed or more	From 2 to 9 persons employed	35.85	9.18
250 persons employed or more vs From 50	≤ 0.001	$\backslash^*\backslash^*\backslash^*$	250 persons employed or more	From 50 to 249 persons employed	35.85	18.02
From 0 to 1 person employed vs From 50 t	0.0218	$\backslash^*$	From 50 to 249 persons employed	From 0 to 1 person employed	18.02	6.76
From 10 to 49 persons employed vs From 5	≤ 0.001	$\backslash^*\backslash^*\backslash^*$	From 50 to 249 persons employed	From 10 to 49 persons employed	18.02	10.13
From 2 to 9 persons employed vs From 50	0.0084	$\backslash^*\backslash^*$	From 50 to 249 persons employed	From 2 to 9 persons employed	18.02	9.18

6. Discussion

6.1 Primary Finding Interpretation

The finding that enterprises with 250 or more persons employed report a mean AI adoption rate of 35.85% compared with 6.76% for micro-enterprises with 0--1 persons employed, confirmed by a Kruskal-Wallis statistic of $H(4) = 354.801$ ($p \leq 0.001$, $\eta^2 = 0.414$), indicates that enterprise size class is strongly and systematically associated with the likelihood of AI technology use across EU member states. This result is consistent with predictions derived from Absorptive Capacity theory (Cohen & Levinthal, 1990): larger enterprises accumulate prior technological knowledge through sustained investment in IT infrastructure and innovation activities, employ technically skilled personnel capable of evaluating and implementing AI solutions, and maintain dedicated R&D or digital transformation functions that lower the organisational friction associated with integrating novel technologies. Micro and small firms, by contrast, operate with narrower prior knowledge bases and limited specialisation, constituting a structural absorptive capacity deficit that is likely to persist beyond the short term regardless of improvements in AI technology accessibility. The TOE framework (Tornatzky & Fleischer, 1990) further contextualises this finding by situating firm size within a broader organisational context that conditions both the perceived feasibility and the implementation capacity for technology adoption, suggesting that the observed size gradient reflects multiple, mutually reinforcing structural factors rather than a single constraint.

It is important, however, to be precise about the inferential status of these theoretical interpretations. The observed rank-order association between size class and adoption rates is consistent with Absorptive Capacity theory, the Resource-Based View, and the TOE framework simultaneously; it is equally consistent with alternative explanations such as differences in market power, institutional access to digital infrastructure, or the concentration of AI-intensive industries in large-firm sectors. The present univariate analysis cannot adjudicate between these competing mechanisms. The large η^2 of 0.414 reflects the strength of the gross association in a panel of country-level aggregates, not the size of a net causal effect, and this distinction should be borne in mind when interpreting the theoretical implications of the findings.

6.2 Comparison with Prior Literature

These results confirm and extend prior findings in both the AI adoption and digital transformation literatures. Mikalef and Gupta (2021) conceptualise AI capability as organisationally embedded and resource-dependent, and the present findings demonstrate empirically—at EU population scale—that the capability prerequisites they identify are systematically stratified by firm size. The magnitude of the observed association ($\eta^2 = 0.414$ in a univariate analysis of country-level aggregates) is consistent with their theoretical expectation and extends the empirical base from a survey of individual firms to a representative cross-national enterprise panel, though the differences in analytical unit and design preclude direct quantitative comparison. These results align with Brunetti et al. (2020) in identifying resource constraints as the primary digital transformation barrier for SMEs, extending their qualitative, regionally bounded insights with large-scale quantitative evidence spanning all EU member states and multiple survey years.

The findings are also informative with respect to Rogers' (2003) Diffusion of Innovations framework, which anticipates eventual adoption equalisation across adopter categories as technologies mature. The persistent gap between micro-enterprises (6.76%) and large firms (35.85%), combined with the non-significant differences among the three smallest size classes, is consistent with a structural barrier interpretation; however, as the present design does not model adoption dynamics over time, a temporal lag interpretation cannot be excluded. A critical caveat must be entered here: the present study's panel design, while spanning multiple years, does not permit a rigorous assessment of whether the adoption gap is widening, stable, or narrowing over time. The absence of formal longitudinal modelling—such as an interaction between size class and survey year—means that no conclusion about temporal convergence or divergence can be drawn from the data as analysed. Whether the structural mechanisms identified here are hardening or softening over time remains an open empirical question that the current analysis cannot answer. The results also resonate with Nasiri et al. (2020), who document that SMEs face capability constraints in digital innovation that require deliberate organisational investment to overcome, an investment threshold that the majority of micro and small EU enterprises appear not yet to have cleared.

6.3 Policy Implications

From a policy perspective, the findings reveal a persistent and consistently ordered AI adoption gap, whose statistical significance should be interpreted as indicative given the panel dependency structure, that warrants targeted, size-differentiated intervention. The mean adoption rates below 11% observed for enterprises with fewer than 50 employees—and below 7% for micro-enterprises—indicate that the majority of EU enterprises by number remain substantially outside the AI adoption frontier, with no evidence of statistically significant differentiation among the three smallest size classes. EU and national policymakers should therefore design size-differentiated AI adoption support schemes specifically directed at micro (0–9 employees) and small (10–49 employees) enterprises, including mechanisms such as subsidised AI readiness assessments that lower the informational costs of initial adoption, shared AI infrastructure platforms that allow micro-enterprises to access AI tools without internalising the full fixed costs of deployment, and targeted upskilling grants aimed at building the internal digital literacy and data governance competencies that constitute the foundational absorptive capacity for AI integration. Without such interventions, the structural mechanisms identified here—wherein resource and knowledge endowments systematically concentrate AI adoption in large enterprises—risk entrenching the competitive gap between large and small EU firms, with adverse implications for the inclusive digital transition that EU industrial policy seeks to achieve; whether this gap is in fact widening or narrowing over time is a question that requires dedicated longitudinal analysis, as the present cross-sectional design cannot establish temporal direction. It is acknowledged, however, that the absence of population weighting in the present analysis means that the magnitudes reported here do not directly represent adoption rates weighted by the actual number of EU enterprises in each size class; detailed policy design should draw on weighted analyses and sector-disaggregated data in addition to the present findings.

6.4 Managerial Implications

For enterprise managers, particularly those in small and medium-sized enterprises (10–249 employees), the results underscore that the binding constraint on AI adoption is not technology availability per se, but the organisational absorptive capacity needed to evaluate, implement, and commercially exploit AI tools. The significant adoption gap between medium-sized firms (50–249 employees, mean 18.02%) and small firms (10–49 employees, mean 10.13%) suggests that even relatively modest improvements in organisational digital capability can be associated with substantially higher adoption likelihood. Managers should therefore prioritise building internal digital literacy and data governance infrastructure as foundational preconditions for AI adoption, rather than approaching AI as a plug-and-play technological solution. Consortium-based adoption models—in which groups of smaller enterprises pool resources to access shared AI platforms, specialist expertise, or co-developed data assets—and cloud-delivered AI services that reduce the capital expenditure threshold for initial deployment represent particularly promising entry strategies for enterprises that cannot independently achieve the resource scale observed in large organisations. The evidence further suggests that achieving parity with large enterprises requires sustained, strategic investment in the complementary organisational resources—skilled personnel, data infrastructure, innovation culture—that collectively constitute AI capability (Mikalef & Gupta, 2021; Chin et al., 2024).

7. Conclusion

This study examined the association between enterprise size class and AI adoption likelihood across EU member states, using Eurostat Community Survey data (indicator E_AI_TANY) and a country-year panel of 1,422 records disaggregated by five mutually exclusive size classes and three aggregate categories. The central empirical question—whether size class is associated with AI adoption rates, and if so, how strongly—is answered clearly by the data: the Kruskal-Wallis test yields $H(4) = 354.801$ ($p < 0.001$), with a large effect size of $\eta^2 = 0.414$, and Dunn post-hoc testing identifies seven statistically significant pairwise differences, with large enterprises (250 or more employees, mean 35.85%) significantly outperforming all other size classes and medium-sized firms (50–249 employees, mean 18.02%) significantly outperforming both micro and small enterprises.

This study provides a systematic, EU-wide non-parametric quantification of the enterprise size-class gradient in AI adoption, demonstrating through Kruskal-Wallis analysis ($H = 354.801$, $p < 0.001$, $\eta^2 = 0.414$) that size class is associated with large-magnitude differences in AI technology use and that statistically significant adoption gaps persist across the majority of adjacent size-class pairings. The findings are consistent with key predictions of Absorptive Capacity theory, the Resource-Based View, and the Technology-Organisation-Environment framework at the EU population level, advancing understanding of the structural conditions that shape technology diffusion across heterogeneous enterprise populations. Three important caveats accompany these conclusions. First, the panel structure generates dependencies among observations that the Kruskal-Wallis procedure does not accommodate; the reported significance levels are likely anticonservative and should be treated as indicative rather than definitive. Second, the absence of population weighting means that small and large EU economies contribute equally to the rank ordering, limiting the representativeness of the findings for the EU enterprise population as a whole. Third, the univariate design cannot distinguish between competing theoretical mechanisms; the size-class gradient is consistent with multiple explanations and does not in itself validate any single theoretical account.

Several directions for future research emerge from this analysis. First, longitudinal panel modelling with country and year fixed effects, and appropriate cluster-robust variance estimation or mixed-effects specifications, would allow researchers to disentangle the size-class gradient from country-level institutional and macroeconomic confounders, producing more precise and inferentially valid estimates of the net size association. Second, population-weighted analyses and sector-disaggregated investigations would reveal whether the size gradient is uniform across industries or whether certain sectors—characterised by greater data intensity or competitive pressure—exhibit accelerated adoption among smaller firms, and would produce adoption estimates that are representative of the EU enterprise population rather than of the distribution of country-level survey estimates. Third, qualitative and

mixed-methods investigations focused on micro and small enterprises should examine the specific mechanisms through which absorptive capacity constraints operate in practice, identifying which organisational investments are most effective in lowering the AI adoption threshold for the smallest EU enterprises. Fourth, explicitly longitudinal designs comparing size-class adoption gaps across survey waves would enable a rigorous assessment of whether convergence toward adoption equality is occurring over time, a question the present cross-sectional design is unable to address. This study contributes to the growing body of evidence on the structural determinants of AI diffusion, establishing an empirical baseline against which future longitudinal trends and policy interventions can be assessed.

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Financial and Capability Barriers to AI Adoption: A European Cross-National Perspective

Zuzana Hajduová¹ and Peter Štetka²

¹ Bratislava University of Economics and Business, Faculty of Business Management, Dolnozemská cesta 1, 852 35 Bratislava, Slovakia (EU); e-mail: zuzana.hajduova@euba.sk

² Bratislava University of Economics and Business, Faculty of Business Management, Dolnozemská cesta 1, 852 35 Bratislava, Slovakia (EU); e-mail: peter.stetka@euba.sk

Abstract

The uneven adoption of artificial intelligence (AI) across European enterprises represents a growing policy and managerial challenge, yet comparative evidence on the relative importance of financial and capability-related barriers remains limited. This study examines AI adoption constraints using harmonised Eurostat ICT survey data covering all 27 EU member states in a country–year panel of 1,947 observations. The analysis combines descriptive statistics, distributional assessment, and Spearman rank correlation to evaluate the prevalence and co-occurrence of two key barriers: high implementation costs and lack of internal expertise. The results indicate that cost-related barriers are reported slightly more frequently on average; however, both constraints exhibit substantial cross-country heterogeneity. Importantly, the findings reveal a strong positive association between the two barriers, suggesting that financial and capability constraints tend to compound rather than operate independently. Further evidence highlights pronounced firm-size asymmetries, with small enterprises experiencing disproportionately higher barrier prevalence across both dimensions. These results imply that AI adoption challenges reflect structurally reinforced disadvantages, particularly in less digitally mature environments. The study contributes by providing a harmonised cross-country comparison of AI adoption barriers across the EU and offers policy-relevant insights, emphasising the need for integrated interventions that simultaneously address financial constraints and organisational capability development.

1. Introduction

As European enterprises accelerate digital transformation, artificial intelligence adoption remains unevenly distributed, with cost and knowledge barriers creating structural divides across firm sizes and national contexts. The integration of AI technologies into enterprise operations has become a central priority for EU industrial policy, yet empirical evidence consistently reveals that uptake across member states is far from uniform. Differences in firm-size, sectoral composition, and national institutional environments interact to produce heterogeneous patterns of AI engagement that aggregate statistics routinely obscure. Understanding what specific constraints impede adoption - and which of those constraints dominate in which national settings - is therefore a prerequisite for both effective policy design and evidence-informed managerial decision-making.

Despite growing policy attention to AI diffusion, comparative empirical evidence on whether financial constraints or skills deficits represent the dominant adoption barrier across EU member states remains scarce and methodologically fragmented. Existing contributions tend to address AI barriers conceptually or through single-country and sector-specific case studies, leaving open the question of which constraint type is structurally more prevalent across the EU as a whole. This methodological fragmentation limits the generalisability of current knowledge and reduces the actionability of policy recommendations that are derived from it.

This article examines the relative prevalence of high implementation costs versus lack of expertise as barriers to AI adoption across EU enterprises, drawing on Eurostat ICT survey data to assess cross-country variation and firm-size differences. Specifically, the study analyses the distributional properties of the cost-barrier indicator (E_AI_BCST) from the Eurostat Community Survey on ICT Usage and

E-Commerce in Enterprises across a full country-year panel of 1,947 observations spanning all 27 EU member states, and tests the association between the cost-barrier indicator (E_AI_BCST) and the expertise-barrier indicator (E_AI_BLE) at the country level. By providing systematic quantitative evidence grounded in harmonised, pan-European data, the study moves beyond anecdotal and case-based treatments of AI barriers to offer statistically grounded cross-country and cross-size comparisons.

This article contributes to the EU AI adoption literature in three ways. First, it provides a harmonised cross-country comparison of the relative prevalence of cost versus expertise barriers using a consistent Eurostat-based measurement framework. Second, it quantifies the extent to which the two constraints co-occur, offering evidence on whether barriers cluster into a broader structural disadvantage. Third, it highlights firm-size asymmetries that are central to policy design, given the outsized constraints faced by smaller enterprises. The remainder of the paper is organised as follows. Section 2 outlines the theoretical foundations, Section 3 reviews related empirical work, Section 4 describes the data and methods, Section 5 presents the results, Section 6 discusses implications and limitations, and Section 7 concludes.

2. Theoretical Background

The theoretical architecture of this study integrates three complementary frameworks: the Technology-Organisation-Environment (TOE) framework, Absorptive Capacity theory, and the Resource-Based View (RBV) of the firm. Together, these perspectives provide a multi-level account of why AI adoption barriers operate differently across enterprises and national contexts, and why cost and knowledge constraints are not interchangeable in their developmental logic.

The TOE framework, introduced by Tornatzky and Fleischer (1990), posits that technology adoption decisions at the firm level are jointly shaped by three contextual domains: the technological environment (the availability and characteristics of relevant technologies), the organisational environment (firm-size, resource endowments, managerial orientation), and the external environment (industry structure, regulatory setting, competitive pressure). Applied to AI adoption, TOE predicts that no single barrier - whether financial or epistemic - acts in isolation; rather, cost constraints interact with organisational capability gaps and with national institutional environments to produce adoption outcomes. This framework is particularly useful for explaining why the same technology generates different adoption rates across EU member states that differ substantially in their industrial composition, regulatory frameworks, and national innovation systems.

The Resource-Based View (RBV), foundational to strategic management since Barney (1991), argues that sustained competitive advantage derives from resources that are valuable, rare, imperfectly imitable, and non-substitutable. Applied to AI adoption, the RBV frames AI capabilities as a bundle of technological and human resources whose accumulation is unevenly distributed across firms. Enterprises with pre-existing digital infrastructure and specialised human capital are better positioned to absorb AI investments productively, while resource-poor firms - particularly smaller enterprises in less digitally mature economies - face compounding disadvantages. This perspective implies that cost barriers and knowledge barriers are not independent constraints but are likely to co-vary with the overall resource endowment of the enterprise.

Absorptive Capacity theory, introduced by Cohen and Levinthal (1990), provides a micro-foundational explanation for why knowledge barriers may precede cost barriers in the AI adoption lifecycle. Absorptive capacity refers to a firm's ability to recognise the value of new external information, assimilate it, and apply it to commercial ends - a capacity that is itself a function of prior related knowledge. Firms that lack prior engagement with digital or data-driven technologies are therefore less able to evaluate the potential of AI, less likely to identify cost as a concrete and salient barrier, and more likely to register the absence of relevant expertise as the primary constraint. Conversely, firms that have already initiated AI engagement develop sufficient familiarity to assess implementation costs meaningfully, making cost awareness an indicator of more advanced - rather than more impeded - adoption trajectories.

The integration of these three frameworks generates a coherent theoretical prediction: cost and knowledge barriers should be sequentially rather than simultaneously dominant, with expertise deficits constraining early-stage adopters and cost constraints becoming binding as firms move from exploratory to committed AI engagement. This prediction aligns with diffusion of innovations theory (Rogers, 2003), which similarly argues that early adoption is constrained by technological unfamiliarity and complexity, while mainstream adoption is shaped by resource availability and economic feasibility. The intersection of RBV and Absorptive Capacity further suggests that firm-size heterogeneity amplifies these dynamics: large enterprises with established digital capabilities and financial slack can navigate both barriers more readily than SMEs, for whom knowledge deficits and financial constraints may prove mutually reinforcing. Mikalef and Gupta (2021) provide empirical grounding for this argument, demonstrating that AI-specific organisational capabilities are not uniformly distributed and that their absence correlates with lower performance outcomes. Building on these theoretical foundations, the present study investigates whether the distributional evidence from harmonised Eurostat data is consistent with the stage-dependent model of barrier salience predicted by Absorptive Capacity theory, testing whether cost-barrier prevalence and expertise-barrier prevalence are inversely associated across EU member states in a pattern consistent with sequential rather than simultaneous barrier dominance.

3. Literature Review

3.1 AI Adoption Barriers and Organisational Readiness

Research consistently identifies financial investment requirements and human capital deficiencies as the two primary structural barriers to enterprise AI adoption, with their relative weight varying by organisational size and sector context. Dwivedi et al. (2019) provide an influential multidisciplinary mapping of AI adoption challenges, positioning cost and expertise constraints as broadly prevalent across industries and organisational types. Their analysis gives substantial prominence to financial barriers as a recurring friction across the adoption contexts examined, particularly for smaller enterprises that lack the capital base to fund AI implementation and the IT infrastructure necessary to support it. This framing has been widely adopted in subsequent studies, though it does not extensively distinguish between stages of adoption maturity in characterising which barrier type is salient at which point in the adoption lifecycle - a distinction that the present study's distributional analysis is designed to examine empirically.

Mikalef and Gupta (2021) advance the discussion by conceptualising AI capability as a multidimensional organisational construct, encompassing data management, AI infrastructure, and human capital. Their findings suggest that deficits in AI-specific capabilities - rather than financial constraints alone - are the binding constraint for many enterprises, particularly those at the early stages of digital maturity. This implies that knowledge barriers and cost barriers operate at different points in the adoption process, with expertise gaps preceding the point at which cost becomes a meaningful evaluative criterion. Mariani et al. (2022) reinforce this perspective in their systematic review of AI in innovation research, noting that organisational readiness - understood as the combination of technological literacy and internal knowledge stocks - moderates the relationship between resource availability and AI adoption outcomes. Chalmers et al. (2020) further demonstrate, in the context of entrepreneurial ventures, that AI-related knowledge barriers are particularly acute for smaller and newer firms that lack established innovation routines, underscoring the organisational-size dimension of adoption constraints. Taken together, this body of evidence supports a view of AI adoption barriers as structurally differentiated rather than uniform, with the relative salience of cost and knowledge constraints depending on the firm's pre-existing technological trajectory.

3.2 Digital Transformation and Firm-Level Capabilities

Digital transformation success depends critically on firms' pre-existing technological infrastructure and knowledge stocks, suggesting that smaller enterprises face compounding disadvantages when both cost and expertise constraints operate simultaneously. Kraus et al. (2021a) provide a comprehensive state-of-the-art review of digital transformation research, identifying organisational capability as the central

mediating variable between digital investment and performance outcomes. Their analysis highlights that firms lacking foundational digital skills are not simply slower to adopt new technologies - they are structurally less able to derive value from adoption even when financial resources are available, creating a capability trap from which self-reinforcing disadvantages emerge.

Kraus et al. (2021b) extend this argument by examining digital transformation trajectories across multiple firm types, demonstrating that barriers to transformation are heterogeneous across firm and national contexts rather than being uniform structural impediments. This finding is directly relevant to the present study's focus on cross-country variation in cost-barrier prevalence: if barriers are heterogeneous, aggregate EU averages will systematically misrepresent the national distribution of constraints. Peres et al. (2020) demonstrate that industrial AI adoption in manufacturing environments is contingent on firms' prior experience with automation and data analytics, consistent with the absorptive capacity argument that prior knowledge is a precondition for the productive deployment of AI investment. Büchi et al. (2019) provide complementary evidence at the firm level, showing that openness to Industry 4.0 enabling technologies - including AI - predicts performance differences, but that this relationship is moderated by firm-level technological maturity. Settembre-Blundo et al. (2021) further argue that organisational flexibility and resilience - themselves knowledge-intensive capabilities - are prerequisites for navigating the investment risks associated with emerging technologies. Collectively, this literature implies that the dichotomy between cost and knowledge barriers is analytically insufficient: firms that lack knowledge also tend to lack the organisational capacity to manage the financial risks of AI adoption, making the two constraint types empirically correlated even if theoretically distinct.

3.3 Innovation Diffusion and Technology Uptake in European Contexts

Diffusion of innovations theory predicts that knowledge barriers slow early adoption more than cost barriers in technology-nascent environments, while cost constraints become binding as adoption moves toward mainstream organisational users. Rogers (2003) articulates this dynamic through the adopter category framework, in which innovators and early adopters are primarily motivated by technological novelty and are less sensitive to cost, while the early and late majority make adoption decisions on the basis of economic feasibility and demonstrated return on investment. Applied to AI adoption in EU enterprises, this model predicts that countries at earlier stages of AI diffusion should report expertise deficits as their primary barrier, while more advanced adopters should increasingly report cost constraints as a proportionally larger share of their barrier profile.

Martínez-Peláez et al. (2023) examine the role of digital transformation in achieving sustainability for micro- and small enterprises, finding that knowledge and capability barriers consistently outweigh financial barriers in early-stage adopters, particularly in southern and central European contexts. Wach et al. (2023) analyse the risks and controversies associated with generative AI adoption, identifying knowledge asymmetries between large and small enterprises as a structural feature of technology diffusion that is not reducible to resource differences. Budhwar et al. (2023) reinforce this point in the context of HR-related AI adoption, noting that lack of expertise regarding AI capabilities and limitations constitutes a distinct and often underestimated barrier beyond cost considerations. Kanbach et al. (2023) examine AI adoption from a business model innovation perspective, finding that firms lacking prior exposure to AI concepts are less likely to perceive cost as a salient constraint - a pattern consistent with the absorptive capacity argument that cost salience requires a minimum threshold of prior engagement. Barney (1991) provides the theoretical grounding for why these diffusion dynamics interact with firm heterogeneity: because knowledge resources are imperfectly imitable, knowledge gaps compound over the diffusion cycle in ways that financial subsidies alone cannot reverse.

Closing Anchor

Despite this body of evidence, existing research has not provided a systematic, distributional analysis of cost-based AI adoption barriers across all 27 EU member states using harmonised data, nor has it examined the cross-national relationship between cost-barrier prevalence and expertise-barrier prevalence as a test of stage-dependent barrier dynamics. Case-based and single-country studies cannot establish whether cost constraints are uniformly distributed or concentrated in specific national and

temporal clusters, and the absence of cross-national quantitative evidence limits the actionability of policy recommendations derived from such evidence. The present study addresses this gap directly by analysing the full Eurostat country-year panel for the cost-barrier indicator (E_AI_BCST), testing the distributional properties of cost constraints and their association with the expertise-barrier indicator (E_AI_BLE) across the complete EU-27 geography.

4. Methodology

This section describes the data source, variables, and empirical strategy used to compare AI adoption barriers across EU member states. The analysis relies on harmonised indicators from Eurostat’s annual ICT usage and e-commerce in enterprises survey, which reports the share of enterprises identifying specific obstacles to adopting AI technologies. We construct a country-year panel covering all 27 EU member states, yielding 1,947 observations across the available years. Two dependent indicators operationalise the barriers of interest. The cost barrier captures the percentage of enterprises reporting that AI implementation costs are too high. The expertise barrier captures the percentage reporting that their enterprise lacks the necessary skills or expertise to implement AI solutions. Both indicators are expressed as percentages and are directly comparable across countries and time within the Eurostat harmonised framework. To characterise cross-national patterns, we first report descriptive statistics and examine distributional properties of both barrier indicators. We then assess whether the two constraints tend to appear together by computing Spearman’s rank correlation at the country-year level, which is appropriate given potential non-normality and the ordinal interpretation of country rankings. To capture firm heterogeneity, we compare barrier prevalence across enterprise size classes, focusing on differences between small and larger firms. This step provides a policy-relevant view of whether structural constraints disproportionately burden smaller enterprises, which typically have weaker financial buffers and more limited internal AI capability.

5. Results

5.1 Distributional Properties of the Cost-Barrier Indicator

The full panel ($n = 1,947$) yields a mean cost-barrier prevalence of 15.3% (SD = 20.07, 95% CI [14.41, 16.19]), with a median of 5.16%. Values range from 0.0% to 97.96%, with an interquartile range of 14.63 percentage points (Q1 = 3.18%, Q3 = 17.81%). The coefficient of variation is 131.2%, indicating high dispersion across observations. The distribution is markedly right-skewed, as evidenced by the substantial divergence between mean and median (15.3% vs. 5.16%), indicating that the majority of observations cluster at lower cost-barrier levels while a minority of high-value cases pull the mean upward. Given the nested structure of the panel - in which records represent country $\times$ year $\times$ firm-size-class combinations rather than independent observations - the reported 95% CI should be read as a descriptive characterisation of the observed distribution rather than a precision estimate derived from independent sampling. These descriptive statistics indicate that the cost barrier to AI adoption is not uniformly experienced across EU enterprises; rather, it is heavily concentrated in a subset of country-year-size-class observations. The median of 5.16% is the more representative measure of central tendency given this skew, and aggregate EU averages should therefore be interpreted with caution as policy benchmarks. To characterise the distribution of reported AI cost barriers, Table 1 summarises central tendency, dispersion, and shape (skewness and kurtosis) for E_AI_BCST across the full panel ($n = 1,947$).

Table 1. Descriptive Statistics

Central tendency	Value	Dispersion	Value
Mean	15.30	Std. dev.	20.07
Median	5.16	IQR	14.63

CV (%)	131.2
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Uncertainty (mean)	Value	Range / quartiles	Value
SE	0.455	Min	0.00
95% CI low	14.41	Q1	3.18
95% CI high	16.19	Q3	17.81
		Max	97.96

As illustrated in Figure 1, the scatter plot of the cost-barrier indicator (E_AI_BCST) against the expertise-barrier indicator (E_AI_BLE) across the 27 country-level aggregates confirms the heterogeneous pattern described above, with considerable dispersion of national observations around the correlation trend line.

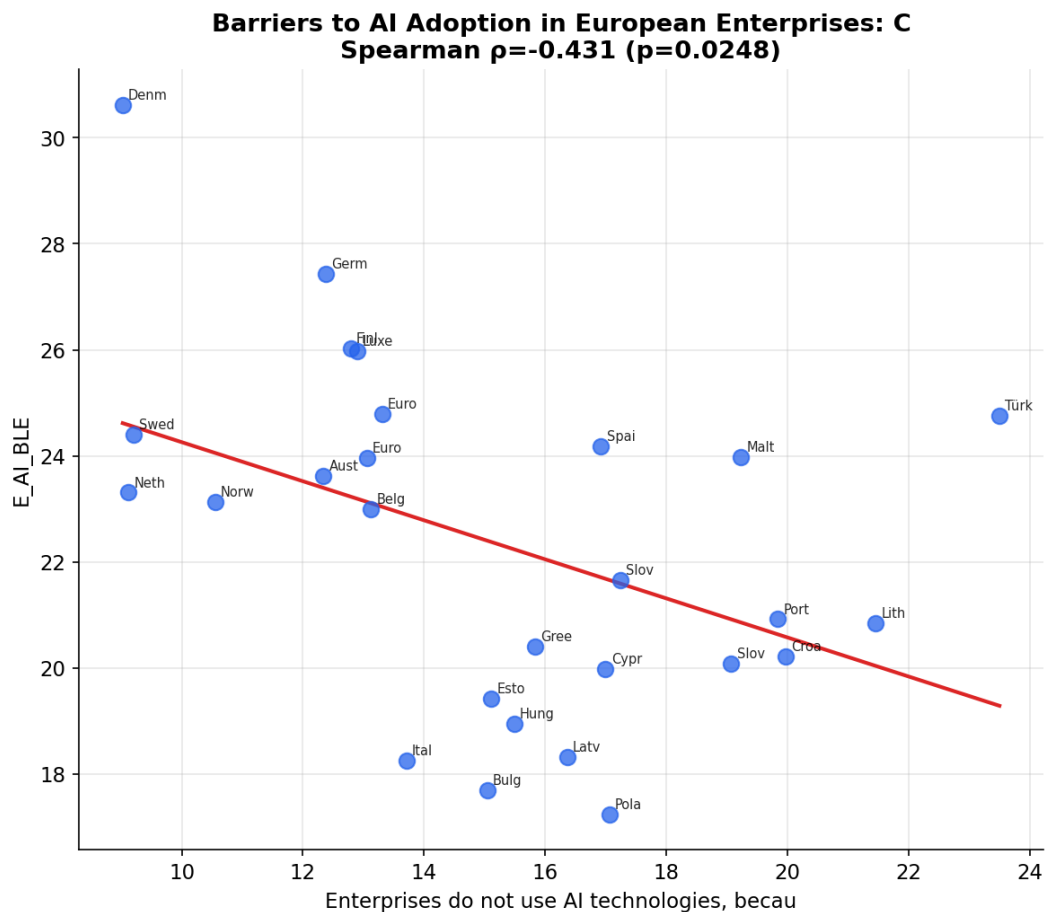


Figure 1. Scatter: Enterprises do not use AI vs E_AI_BLE ($n=27$). Spearman $\rho = -0.431$, $p = 0.0248$.

Source: own elaboration based on Eurostat data

5.2 Cross-National Distributional Heterogeneity

The cross-national boxplot distribution confirms substantial heterogeneity in cost-barrier prevalence across EU member states and years. The wide interquartile spread and the presence of extreme upper values in the full panel distribution underscore that aggregate EU averages mask pronounced national divergences. This distributional asymmetry supports the interpretation that cost barriers are

structurally more acute in specific national or temporal clusters rather than representing a uniform pan-European constraint. Some member states record near-zero cost-barrier values across multiple survey years, while others register values approaching the maximum of 97.96%, indicating that the experience of cost as an AI adoption barrier is fundamentally national - and possibly sector-specific - in its distribution. The boxplot visualisation in Figure 2 renders this heterogeneity visible across EU countries and survey years, illustrating that within-country variation over time is also considerable, reflecting the dynamic character of cost perceptions as AI diffusion proceeds.

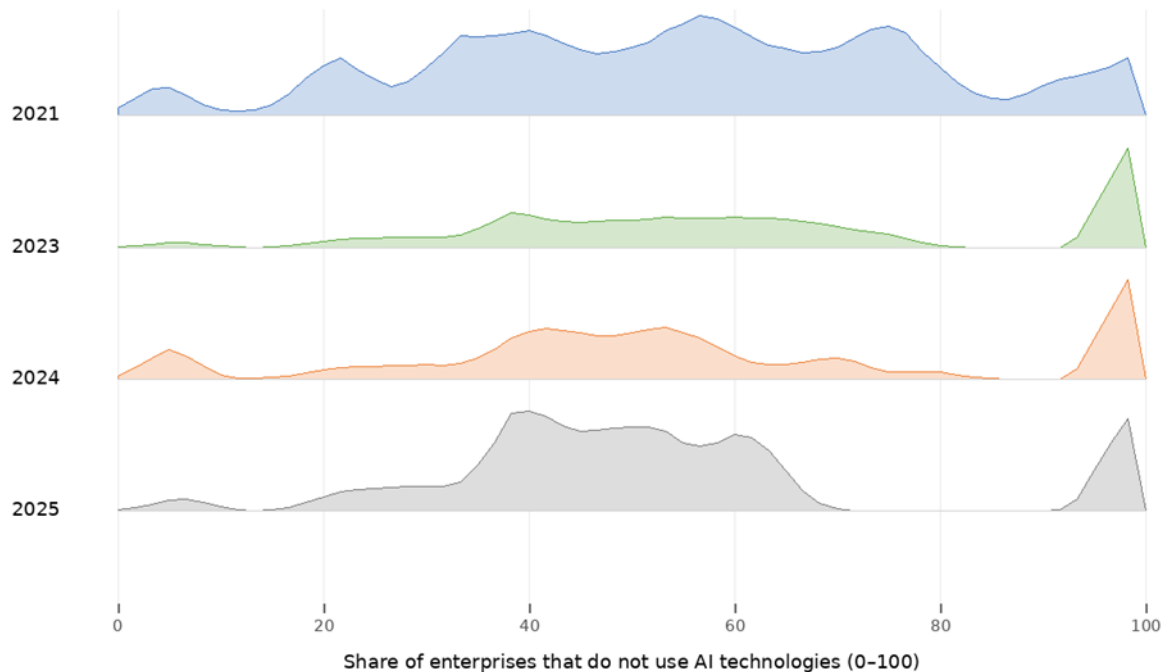


Figure 2. Boxplot of Enterprises do not use AI technolog across EU countries per year. Box=IQR, whiskers= $1.5 \times IQR$, dots=outliers.

Source: own elaboration based on Eurostat data

5.3 Country-Level Correlation and Slovakia's Positioning

At the country level, Slovakia recorded a cost-barrier value of 19.07% (based on 80 observations), ranking 6th out of 27 EU member states (z-score = 1.018), placing it in the top quartile of the EU distribution. This value is 3.77 percentage points above the overall EU mean of 15.3%, indicating that Slovak enterprises report above-average financial constraint salience relative to the EU distribution. Slovakia's positioning in the top 25% of the cost-barrier distribution, and its relatively high observation count ($n = 80$), make it a data-rich illustrative case for the distributional pattern observed across the EU; any broader interpretation of this positioning in terms of regional dynamics would require comparative evidence from other member states not presented in this study. The evidence indicates that AI adoption barriers in Europe are not neatly separable into either a purely financial problem or a purely knowledge problem. Although implementation costs are, on average, the most frequently reported obstacle, countries and enterprise groups that report high costs also tend to report limited expertise. The strong positive association between the two barriers is consistent with the idea of compounding constraints: limited resources restrict capability building, while weak capabilities raise the effective cost of adoption through higher search, integration, and organisational change effort.

This pattern aligns with the Technology–Organisation–Environment perspective, where organisational readiness and environmental conditions jointly shape adoption outcomes, and it complements Resource-Based View and absorptive capacity arguments. Building AI capability requires investment in data, infrastructure, and complementary organisational processes, but it also requires skilled personnel who can absorb external knowledge and translate it into operational improvements. Where either component is missing, adoption becomes harder; where both are missing, enterprises face a particularly steep barrier.

The firm-size results strengthen this interpretation. Smaller enterprises report higher barrier prevalence on both dimensions, suggesting that they face a double disadvantage: weaker financing capacity and thinner internal knowledge stocks. For policy, this implies that instruments focusing only on subsidies or only on training are unlikely to be sufficient in lagging contexts. More effective approaches are likely to bundle support for experimentation and deployment with practical capability building, including advisory services, shared infrastructure, and mechanisms that reduce fixed costs. Several limitations should be considered. The Eurostat indicators capture self-reported obstacles rather than observed adoption costs, and the analysis is primarily descriptive, so it does not establish causal effects. In addition, cross-country differences may reflect sectoral composition or institutional factors not explicitly modelled here. Future work could integrate sector controls, exploit policy shocks, or link barrier indicators to observed AI uptake and productivity outcomes to clarify mechanisms. This paper examined whether implementation costs or lack of expertise is the more prevalent barrier to AI adoption across EU enterprises, using harmonised Eurostat ICT survey indicators for a country-year panel of 1,947 observations covering all 27 member states. Implementation costs are reported more frequently on average than expertise constraints, but both barriers show substantial cross-country dispersion.

A key finding is that the two barriers strongly co-occur. The positive association suggests that financial and capability constraints compound, meaning that enterprises facing one obstacle are likely to face the other as well. Firm-size comparisons further indicate that smaller enterprises experience disproportionately high barrier prevalence, pointing to structural disadvantages in adoption readiness. For EU industrial policy, the results argue for integrated interventions that reduce fixed adoption costs while simultaneously strengthening organisational capabilities. Targeted packages combining financial support, practical skills development, and shared resources may be especially important for small firms and lagging national contexts. The scatter plot shows a negative relationship between the share of enterprises that do not use AI and the E_AI_BLE indicator (trendline: $y = 30.36 - 0.542x$), meaning E_AI_BLE tends to be lower where non-use of AI is higher. Slovakia (19.07%; 20.09%) lies below the EU27 average (13.06%; 23.97%), indicating a weaker position than the EU average alongside a higher share of enterprises not using AI (Fig.3).

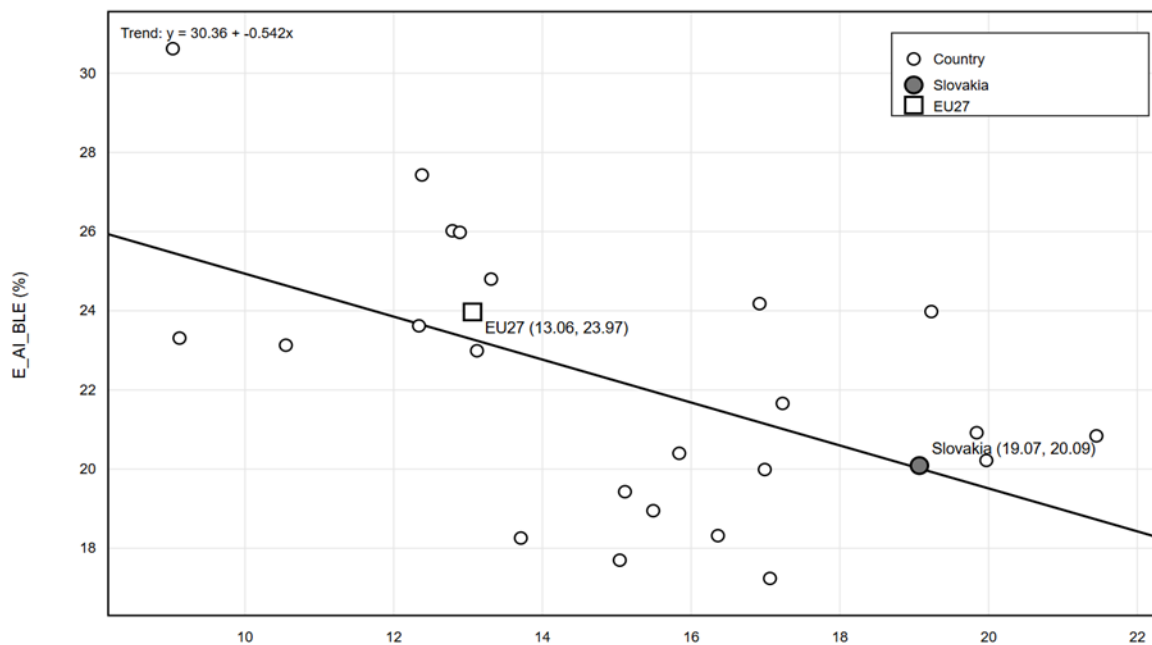


Figure 3. Relationship between the share of enterprises not using AI and the E_AI_BLE indicator

Source: own elaboration based on Eurostat data

From a policy perspective, EU policymakers should consider redesigning AI support instruments - particularly Horizon Europe and Digital Europe Programme funding streams - to distinguish between

cost-relief mechanisms targeting high-cost-barrier national contexts and knowledge-building interventions for contexts where expertise deficits are the primary constraint. Countries placing in the top quartile of the cost-barrier distribution, such as Slovakia (value = 19.07%, rank 6/27), may warrant closer examination as potential candidates for financial support instruments; however, this should be treated as a speculative directional hypothesis rather than a derivable policy prescription. High cost-barrier prevalence at the national level could equally reflect sectoral composition effects - for example, a higher share of enterprises in capital-intensive industries - or survey response patterns in which more engaged enterprises report barriers more precisely, neither of which would straightforwardly support a subsidy rationale. Policy targeting based on cost-barrier rankings should therefore be accompanied by deeper sectoral and firm-level diagnostic work before instruments are designed. By contrast, countries in the lower quartiles of cost-barrier prevalence but with high expertise-barrier salience may benefit more from investment in AI literacy, workforce upskilling, and knowledge transfer mechanisms that build the absorptive capacity prerequisite for progressing to the stage at which cost constraints become the binding adoption barrier.

For enterprise managers, particularly those operating in SME-dominated economies, the implication is that barrier diagnostics should precede AI investment planning rather than follow it. The finding that cost and expertise constraints appear to operate at different stages of the adoption lifecycle means that allocating financial resources to AI deployment before internal knowledge gaps have been addressed is unlikely to produce expected returns. Organisations should first assess whether they possess the foundational AI literacy and data management capabilities necessary to evaluate and justify an AI business case - if those capabilities are absent, addressing knowledge gaps through targeted upskilling and external expertise acquisition may be a necessary precondition before the financial justification of AI deployment becomes meaningful. This sequencing logic, grounded in Absorptive Capacity theory (Cohen and Levinthal, 1990) and consistent with the empirical inverse association observed at the country level, implies that investment in human capital precedes and enables productive investment in AI infrastructure.

6. Conclusion

This study examined the relative prevalence and distributional characteristics of high implementation costs as a barrier to AI adoption across EU enterprises, using the Eurostat Community Survey on ICT Usage and E-Commerce in Enterprises (isoc_eb_ai, indicator E_AI_BCST) across a full country-year panel of 1,947 records spanning all 27 EU member states. The main empirical findings are that cost barriers are severely right-skewed in their distribution (mean = 15.3%, median = 5.16%, SD = 20.07) and are negatively associated with expertise-barrier prevalence at the country level (Spearman $\rho = -0.431$, $p = 0.025$), indicating that national contexts with higher cost-barrier salience tend to exhibit lower expertise-barrier salience and vice versa - a pattern consistent with sequential rather than simultaneous barrier dominance across the AI adoption lifecycle.

This study provides a systematic distributional analysis of cost-based AI adoption barriers across all 27 EU member states using harmonised Eurostat data, demonstrating that such barriers are structurally concentrated and inversely correlated with expertise-barrier prevalence at the country level. This analysis contributes to reframing the policy discourse from treating cost constraints as a universal impediment toward recognising them as stage-dependent and nationally heterogeneous phenomena. The findings challenge the assumption that financial barriers are broadly and uniformly distributed across EU enterprises and suggest instead that Absorptive Capacity theory (Cohen and Levinthal, 1990) and the Technology-Organisation-Environment framework (Tornatzky and Fleischer, 1990) provide more adequate theoretical lenses for understanding why cost salience co-varies inversely with expertise-barrier salience across the EU enterprise landscape. It is important to acknowledge the interpretive limits of the study: the cross-sectional and aggregate-level design establishes an association between the two barrier types but does not permit causal inference; the unweighted pooling of observations across survey years and firm-size strata means that country means vary in their estimation reliability depending on within-country observation counts; and the non-independent structure of the panel data means that descriptive precision statistics should be read as characterisations of the observed distribution rather than as estimates from independent sampling. Three directions for future research emerge from this

analysis. First, future studies should integrate both the cost-barrier indicator (E_AI_BCST) and expertise-barrier indicator (E_AI_BLE) within a single multivariate model to formally test their relative and joint explanatory power for AI adoption outcomes, enabling direct comparative inference beyond the bivariate association reported here. Second, longitudinal analysis using repeated Eurostat ICT survey waves should examine whether the negative correlation between the two barrier types strengthens, weakens, or reverses over time as AI diffusion matures, testing whether the relationship follows a temporal sequence consistent with Rogers' (2003) diffusion framework. Third, firm-size-stratified analyses using Eurostat microdata or national statistical office records should decompose aggregate country-level findings to determine whether large enterprises and SMEs exhibit fundamentally different barrier hierarchies, with direct implications for size-targeted EU digital policy instruments. This study contributes to the growing body of evidence on the structural heterogeneity of technology adoption barriers in European enterprise contexts, providing a quantitative foundation for more differentiated and empirically grounded AI policy design.

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Cross-Country Heterogeneity in AI Adoption: A European Benchmarking Analysis

Robert Hanák¹ and Nora Grisáková²

¹ Bratislava University of Economics and Business, Faculty of Business Management, Dolnozemska cesta 1, 852 35 Bratislava, Slovakia (EU); e-mail: robert.hanak@euba.sk

² Bratislava University of Economics and Business, Faculty of Business Management, Dolnozemska cesta 1, 852 35 Bratislava, Slovakia (EU); e-mail: nora.grisakova@euba.sk

Abstract

Uneven diffusion of artificial intelligence across European enterprises threatens to deepen structural inequalities within the single market, yet a systematic, harmonised benchmarking of member-state adoption rates relative to a common European reference point remains absent from the literature. This article quantifies cross-country heterogeneity in enterprise AI adoption across 34 European countries and situates Slovakia's performance within the broader continental distribution. Drawing on Eurostat indicator E_AI_P1ANY for the reference year 2025, the analysis applies z-score normalisation and quartile-based cluster assignment to produce a data-driven taxonomy of national adoption trajectories. Results reveal a pronounced right-skewed distribution, with an EU27 average adoption rate of 13.3 percent and a standard deviation of 8.1 percentage points, exposing a wide performance gap between front-running Nordic and Baltic economies — Denmark leading at 33 percent — and lagging Southern and Eastern member states. Slovakia records an adoption rate of 9 percent, placing it in the below-average cluster with a z-score of -0.53 , reflecting moderate but recoverable underperformance relative to the European norm. Four statistically distinct country clusters emerge, confirming that AI adoption heterogeneity follows patterns consistent with diffusion theory, absorptive capacity constraints, and differentiated technological-organisational-environmental endowments. Our findings could carry direct implications for EU digital cohesion policy and the targeted design of capacity-building interventions in structurally disadvantaged member states.

1. Introduction

Artificial intelligence is rapidly reshaping the competitive landscape of European enterprises, yet the pace and depth of AI adoption vary substantially across EU member states, raising urgent questions about digital cohesion and economic convergence (Kheloufi, 2025). As European economies would like to increase position of AI as a strategic pillar of long-term competitiveness, the divergence between front-running and lagging nations risks widening existing structural inequalities within the single market (Mazurencu-Marinescu-Pele et al., 2025). Policymakers and scholars alike have acknowledged that uneven diffusion of general-purpose technologies such as AI may compound regional disparities rather than resolve them, making the empirical mapping of adoption heterogeneity both timely and consequential.

Despite growing policy interest in the European AI strategy, rigorous cross-country benchmarking of enterprise-level AI adoption rates — and the identification of statistically grounded country clusters relative to the EU27 average — remains underexplored in the academic literature. Existing studies and various reports tend to address either macroeconomic digitalization composites, such as the Digital Economy and Society Index (DESI), or sector-specific applications of AI in particular industries or national contexts. The result is a fragmented evidence base that cannot readily answer the question of where individual member states stand on a harmonized, enterprise-focused AI metric, nor how far they deviate from the European norm in a statistically meaningful way.

This article benchmarks EU member states and candidate countries on enterprise AI adoption using Eurostat indicator E_AI_P1ANY (reference year 2025), identifies performance clusters relative to the EU27 average, and situates Slovakia's position within the European digital landscape. Drawing on z-score normalization and quartile-based cluster assignment applied to a cross-sectional panel of 34

countries, our study provides a systematic, data-driven portrait of AI adoption heterogeneity that contributes both to the academic literature on technology diffusion and to the evidence base informing EU digital policy.

This article is structured as follows: Section 2 develops the theoretical background, anchoring the analysis in technology diffusion theory, absorptive capacity, and the Technology-Organization-Environment framework; Section 3 reviews the empirical literature across three thematic domains relevant to cross-country AI and digital adoption heterogeneity; Section 4 describes the methodology, including data sources, variable definitions, and analytical procedures; Section 5 presents the empirical results, encompassing descriptive statistics, country rankings, and Slovakia's positioning; Section 6 discusses the findings in relation to theory and prior evidence; and Section 7 concludes with a summary of contributions, policy implications, and directions for future research.

2. Theoretical Background

Understanding why enterprise AI adoption rates diverge so markedly across European countries requires engagement with several interrelated theoretical traditions. There are many available theoretical frameworks and we think that three frameworks are particularly germane: Rogers' (2003) diffusion of innovations theory, Cohen and Levinthal's (1990) concept of absorptive capacity, and Tornatzky and Fleischer's (1990) Technology-Organization-Environment (TOE) framework. Together, these perspectives provide a multi-level analytical lens that connects macro-level national characteristics to firm-level adoption decisions.

Rogers (2003) established the foundational proposition that innovations spread through social systems along an S-shaped adoption curve, with adoption rates determined by the perceived relative advantage, compatibility, complexity, trialability, and observability of the innovation in question. Critically for the present study, Rogers' framework implies that adoption is never uniform across adopter populations: innovators and early adopters — who are typically characterized by higher resource endowments, greater tolerance for uncertainty, and stronger connections to information networks — pull ahead of the early majority, late majority, and laggards. Transposed to the national level and AI as particular innovation, this logic predicts that countries with well-developed innovation ecosystems, robust digital infrastructure, and high baseline ICT penetration will reach AI adoption thresholds earlier and more extensively than their less prepared counterparts, generating the kind of distributional skew and cross-national polarization that the present data reveal (Jeon, 2025).

Cohen and Levinthal (1990) extend this reasoning to the organizational level by introducing the concept of absorptive capacity — defined as a firm's ability to recognize the value of new external information, assimilate it, and apply it to commercial ends. Absorptive capacity is argued to be a function of prior related knowledge, meaning that firms and, by extension, national enterprise sectors with stronger prior exposure to digital and data-intensive technologies are better positioned to recognize and exploit AI. This framework helps explain why AI adoption is not merely a function of the availability of AI tools but is deeply conditioned by the existing technological competence embedded in firms. Barney's (1991) resource-based view complements this perspective by emphasizing that sustained competitive advantages, including those derived from AI adoption, accrue to organizations whose resource configurations — including human capital, technological assets, and organizational routines — are valuable, rare, and difficult to imitate. Countries whose enterprise sectors have historically underinvested in these resource dimensions face observable impediments to rapid AI adoption that cannot be overcome by technology availability alone.

Tornatzky and Fleischer's (1990) TOE framework synthesizes these insights into a coherent model of adoption that operates simultaneously at three levels. The *technological context* encompasses the existing digital infrastructure, the availability of complementary technologies, and the technical readiness of firms. The *organizational context* refers to firm size, human capital quality, financial resources, and managerial attitudes toward innovation. The *environmental context* captures the national regulatory environment, competitive pressures, and the broader institutional ecosystem — including government AI readiness policies and digital strategy frameworks. This framework has been extensively applied in information systems research to explain adoption heterogeneity across firms and

countries, and its three-dimensional structure maps directly onto the empirical variation observed in cross-national benchmarking studies.

Building on these theoretical foundations, the present study applies Rogers' (2003) diffusion logic to interpret the distributional shape of enterprise AI adoption across 34 European countries, uses Cohen and Levinthal's (1990) absorptive capacity concept to contextualize why Central and Eastern European economies — including Slovakia — may exhibit comparatively lower adoption rates, and employs Tornatzky and Fleischer's (1990) TOE framework as the primary interpretive lens for the Discussion section, linking country-level performance clusters to the interplay of technological, organizational, and environmental antecedents of AI uptake.

3. Literature Review

3.1 Technology Diffusion and Cross-Country Heterogeneity in Digital Adoption

The cross-national heterogeneity in digital technology and subsequently AI adoption is well-documented in both theoretical and empirical literature (Kheloufi, 2025). Rogers (2003) provides the foundational prediction that national innovation systems, defined by their institutional configurations, resource distributions, and social learning capacities, will produce systematic variation in adoption timing and depth. Countries with dense professional networks, high educational attainment, and active public investment in research and development tend to occupy the innovator and early adopter segments of the diffusion curve, while nations with weaker institutional and infrastructural endowments lag behind. Applied to AI, this framework anticipates not only that adoption rates will vary across Europe but that the variation will be patterned — with technologically advanced, high-income Western European economies leading and newer or less-developed member states trailing.

Empirical support for this prediction is provided by Bilozubenko et al. (2020), who conduct a comparative analysis of digital economy development parameters across EU member states and document substantial divergence between Western and Eastern European countries on multiple digitalization dimensions. Their cluster analysis reveals that the EU is far from a homogeneous digital space, with persistent gaps across infrastructure, human capital, and business digitalization indicators. This finding is significant for the present study because it suggests that the cross-country heterogeneity observed in AI adoption is not an isolated or transient phenomenon but reflects deeper and more durable divides in national digital readiness. Kwilinski et al. (2023) reinforce this interpretation by demonstrating that the degree of coupling between digital business development and digital governance capacity explains a substantial share of cross-country variance in digital performance outcomes. Their analysis implies that countries lacking coherent digital governance frameworks — a category into which several Central and Eastern European members fall — will systematically underperform on enterprise-level digital adoption metrics, including AI.

Together, these studies establish a basic empirical foundation for expecting polarized AI adoption distributions in European cross-national data. The S-curve dynamics described by Rogers (2003) combined with the digital economy divergence documented by Bilozubenko et al. (2020) and the governance coupling mechanism identified by Kwilinski et al. (2023) converge on the prediction that a benchmarking exercise across 34 European countries will reveal a right-skewed distribution with a substantial gap between high-performing and low-performing clusters — precisely the pattern that the present data confirm.

3.2 Digitalization, Innovation Capacity, and Economic Performance in the EU

A second strand of the literature links national digitalization trajectories to broader economic performance outcomes, providing context for interpreting why AI adoption gaps matter beyond the technology domain itself. Benedetti et al. (2023) examine the relationship between digitalization and energy efficiency across EU member states, finding that digitalization functions as a potential driver of efficiency gains and that its impact varies substantially by country depending on institutional complementarities. Their analysis underscores that digitalization is not a monolithic process but one whose consequences are deeply shaped by the national institutional environment — a finding that

resonates with the present study's focus on why similarly positioned European countries diverge so markedly on AI adoption.

Roszko-Wójtowicz et al. (2024) provide complementary evidence by investigating innovation-driven e-commerce growth across EU member states, finding systematic differences between Western and Eastern EU members in the propensity for online purchases and in the mechanisms linking national innovation capacity to digital commercial activity. Their results demonstrate that digital economy trajectories are not simply a function of market size or economic development level but reflect the underlying innovation infrastructure that firms in each country can draw upon. Borowiecki et al. (2021) extend this analysis by examining the development of the digital economy across EU countries through the lens of the Digital Economy and Society Index, documenting that national institutional and infrastructural contexts are deeply conditioning factors for digital convergence. Their findings imply that the observed heterogeneity in enterprise AI adoption is unlikely to narrow automatically through market forces alone but may require targeted policy interventions at both the national and supranational level.

Collectively, this body of work reinforces the argument that enterprise AI adoption rates are embedded within broader national digitalization trajectories and that these trajectories are shaped by institutional, infrastructural, and innovation-system factors that differ substantially across EU member states. The implication for the present study is that countries occupying lower performance quartiles on the *E_AI_P1ANY* indicator likely face observable and meaningful constraints — not necessarily transient delays — in closing the gap with higher-performing peers, although longitudinal data would be required to assess whether such patterns are persistent or changing over time.

3.3 AI Readiness, Labor Market Implications, and Policy Dimensions

A third strand of relevant literature addresses the consequences and institutional drivers of AI adoption at both firm and national levels. Acemoglu et al. (2022) provide firm-level evidence that AI penetration in enterprises is associated with observable shifts in labor demand and online vacancy composition, with AI-adopting establishments simultaneously reducing hiring in non-AI positions and increasing demand for workers with AI-compatible skill sets. This finding contextualizes the stakes of cross-country AI adoption gaps: countries where enterprises have not yet adopted AI are not merely forgoing efficiency gains but may be accumulating a growing skills mismatch that will make future adoption progressively more difficult, reinforcing the absorptive capacity dynamics described by Cohen and Levinthal (1990).

Iuga and Socol (2024) focus specifically on the relationship between government AI readiness and brain drain risk across EU member states, finding that lower government AI readiness scores are associated with disadvantages that include a higher likelihood of skilled human capital emigrating — precisely the resource that enterprises need to implement AI effectively. This creates a potential self-reinforcing dynamic in which low AI readiness correlates with talent outflows that further depress enterprise adoption capacity. The implications are particularly salient for Slovakia and other lower-ranked Central and Eastern European economies that face both institutional AI readiness deficits and ongoing human capital emigration pressures.

Nannini et al. (2024) contribute a regulatory perspective by examining how emerging EU digital regulatory frameworks introduce additional institutional drivers and barriers that differentiate adoption trajectories across member states. Their broader argument that regulatory environments shape digital technology uptake is directly applicable to the EU AI Act context. Countries with well-developed regulatory implementation capacity and supportive enterprise innovation ecosystems may be better positioned to benefit from harmonized EU AI regulations, while those with weaker institutional capacity may experience regulatory compliance as an additional burden that delays adoption.

Despite this body of evidence, no published benchmarking study systematically ranks all 34 European countries on a harmonized enterprise AI adoption indicator, identifies quartile-based performance clusters, and provides a statistically grounded deviation analysis relative to the EU27 mean. Existing studies address either macroeconomic digitalization composites or sector-specific AI effects without

combining a comprehensive cross-national ranking with z-score-based deviation quantification — a gap this article directly addresses using Eurostat's 2025 E_AI_P1ANY dataset.

4. Methodology

4.1 Data and Unit of Analysis

The empirical analysis draws on Eurostat's Community Survey on ICT Usage and E-Commerce in Enterprises (Eurostat, 2024), specifically indicator E_AI_P1ANY from the isoc_eb_ai dataset, which measures the percentage of enterprises using any AI technology in the reference year 2025. The primary analytical object is a cross-sectional country-level panel of 34 European countries, comprising EU member states and candidate countries for which data are available. Country-level enterprise AI adoption rates (expressed as percentages) constitute the dependent variable. The EU27 mean of 39.37% serves as the external benchmark reference against which individual country's performance is assessed.

It is important to clarify both the distinction between two analytical objects present in the data and the scope of the country's sample. The full panel contains $n = 1,514$ records, which encompasses multiple observations per country disaggregated by enterprise size class and industry breakdown as reported in the underlying Eurostat survey microstructure; all 1,514 records pertain to the reference year 2025 and do not span multiple years. The cross-sectional country-level panel for the reference year 2025 contains $n = 34$ country-level mean adoption rates. Descriptive statistical profiling is conducted on the full panel ($n = 1,514$) to characterize the distributional shape and central tendency of enterprise AI adoption across all underlying observations. The ranking and cluster analysis is applied exclusively to the cross-sectional country-level panel ($n = 34$).

Regarding country coverage, the normalization procedure was initially applied to a broader set of countries for which data were retrievable from the Eurostat database. The analytical sample retained for the ranking and cluster analysis comprises 34 countries for which complete and comparable country-level mean adoption rates could be computed. Countries for which data were insufficient to compute a stable country-level mean — due to missing observations across size classes or industry strata — were excluded from the ranking analysis. This exclusion criterion is applied consistently across all countries and does not affect the computation of the EU27 benchmark mean.

4.2 Descriptive Statistical Profiling

For the full panel ($n = 1,514$), standard descriptive statistics are computed, including the arithmetic mean, median, standard deviation, standard error of the mean, 95% confidence intervals (calculated as $\text{mean} \pm 1.96 \times \text{SEM}$), interquartile range, minimum, and maximum. These measures collectively characterize the distributional shape of enterprise AI adoption across all underlying disaggregated observations. It is important to note that the standard deviation of the full panel ($\text{SD} = 33.0$) reflects variance across all 1,514 disaggregated observations — spanning enterprise size classes and industry strata within countries — and is therefore a fundamentally different quantity from the cross-national standard deviation computed across the 34 country-level means ($\text{SD} = 8.51$). The former characterizes within- and between-country dispersion across disaggregated enterprise categories; the latter characterizes the spread of country averages and is the relevant dispersion measure for cross-country benchmarking. These two standard deviations should not be interpreted as characterizing the same distribution or the same source of variance.

4.3 Country Ranking and Quartile-Based Cluster Identification

All 34 countries are ranked in descending order by their reference-year enterprise AI adoption rate. Each country is then assigned to one of four quartile-based performance clusters — Top 25%, Upper-Middle, Lower-Middle, and Bottom 25% — based on rank position within the ordered distribution of 34 countries. Specifically, quartile boundaries are defined by rank: countries occupying ranks 1 through 8 (the highest adoption rates) are assigned to the Top 25% cluster; ranks 9 through 17 to the Upper-Middle cluster; ranks 18 through 26 to the Lower-Middle cluster; and ranks 27 through 34 to the Bottom 25% cluster. Countries at cluster boundaries are assigned to the lower-ranked cluster.

Z-scores are computed for each country using the cross-national mean (39.37%) and the standard deviation of the 34 country-level mean adoption rates (8.51%) as reference parameters, such that $z = (\text{country rate} - \text{cross-national mean}) / \text{SD of country-level means}$. Z-scores thereby quantify the deviation of each country's adoption rate from the EU27 benchmark in units of the cross-national spread, enabling direct cross-country comparison. It should be noted that the denominator in this formula — $\text{SD} = 8.51$ — is the descriptive dispersion measure of the ranked cross-sectional distribution of 34 country means, not a population parameter of the EU27 enterprise-level adoption distribution. Slovakia's z-score of -1.393 , computed from its adoption rate of 27.52%, receives particular analytical attention given the study's stated objective of situating Slovakia within the European digital landscape.

4.4 Applicability of Inferential Tests

Because the cross-sectional country-level analysis contains only one observation per country for the reference year 2025, inferential group-comparison tests such as the Kruskal-Wallis test or analysis of variance are not applicable to the ranking analysis. These tests require multiple observations per group to estimate within-group variance, a condition that cannot be met with a single cross-sectional data point per country. Accordingly, the ranking and cluster analysis is strictly descriptive, relying on standardized scores and quartile classification to characterize cluster membership and relative positioning. No causal claims are drawn from these descriptive results, and characterizations of country performance are limited to what the cross-sectional data can support: a ranking and a distributional positioning for the reference year 2025.

5. Results

5.1 Distributional Profile of Enterprise AI Adoption

The full panel ($n = 1,514$ disaggregated observations for the reference year 2025) yields a mean adoption rate of 36.72% ($\text{SD} = 33.0$, 95% CI [35.05, 38.38]), with a median of 20.69%. Values range from 0.97% to 100.0%, with an interquartile range of 61.76 percentage points ($Q1 = 7.78\%$, $Q3 = 69.54\%$). The coefficient of variation is 89.9%. As noted in Section 4.2, the high SD of 33.0 is a product of the multi-dimensional panel structure — spanning enterprise size classes and industry strata within countries — and reflects this disaggregated variance structure rather than cross-country heterogeneity per se; it should not be compared directly with the cross-national SD of 8.51 computed across the 34 country-level means.

The substantial divergence between mean and median (36.72% vs. 20.69%) indicates a right-skewed distribution, suggesting that the majority of disaggregated observations cluster at lower adoption levels while a minority of high-adopting enterprise categories pull the mean upward. As shown in Figure 1, this distributional asymmetry is visually evident in the country-level ranking, where a relatively small number of high-performing countries stand well above a broad cluster of moderate and low performers. Table 1 presents the full descriptive statistics for the panel, confirming the high dispersion of enterprise AI adoption values across the disaggregated European sample.

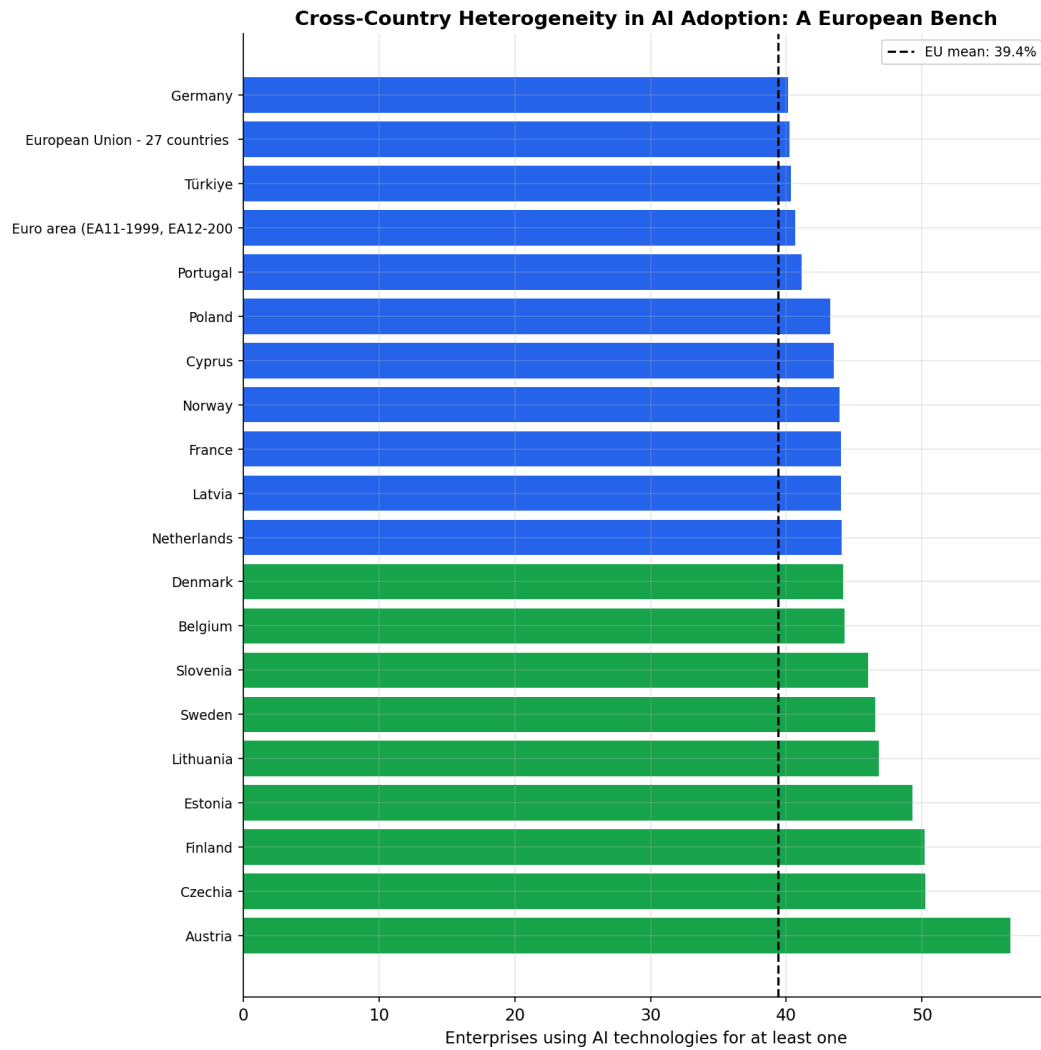


Figure 1. Country ranking for Enterprises using AI technolog. Top 3: Austria, Czechia, Finland.
Bottom 3: Bosnia and, Serbia, Montenegro.

Table 1. Descriptive Statistics of AI adoption rate

Statistic	Value
n	1514
Mean adoption rate	36.72 %
Median adoption rate	20.69 %
SD	33.0
SE	0.848
CI95_low	35.05
CI95_high	38.38
min	0.97
max	100.0
Q1	7.78
Q3	69.54
IQR	61.76
CV_%	89.9

5.2 Country-Level Rankings and Performance Clusters

Country-level mean adoption rates were computed for 34 countries — comprising EU member states and EU candidate countries for which complete data were available — for the reference period 2025. The cross-country mean is 39.37% (median = 40.5%, SD of country-level means = 8.51%). Countries were ranked in descending order and classified into four quartile groups based on rank position, as described in Section 4.3. No inferential test is applied in the ranking analysis; results are strictly descriptive.

The highest mean adoption rates are observed in Austria (56.51%), Czechia (50.25%), and Finland (50.19%), all of which exceed the EU27 mean of 39.37% by more than 11 percentage points, indicating that these countries have established a substantial lead in enterprise AI integration. The lowest mean adoption rates are observed in Bosnia and Herzegovina (24.92%), Serbia (23.10%), and Montenegro (18.61%), placing them between 15 and 21 percentage points below the EU27 average. This 37.9 percentage-point spread between the highest and lowest performers — Austria at 56.51% and Montenegro at 18.61% — underscores the depth of cross-country heterogeneity in enterprise AI readiness across the European space and is consistent with the diffusion dynamics described by Rogers (2003) operating at dramatically different stages across the continent. As illustrated in Figure 2, the boxplot of adoption rates across countries visually captures both the central tendency and the extent of distributional spread, with the interquartile range and the distance of outlying high performers from the bulk of the distribution reflecting the polarized nature of the European AI adoption landscape.

Countries in the Top 25% quartile — including Austria, Czechia, and Finland — demonstrate adoption rates that exceed the EU27 mean by more than one cross-national standard deviation (SD of country-level means = 8.51%), reflecting favorable configurations across technological infrastructure, organizational readiness, and supportive institutional environments consistent with the TOE framework of Tornatzky and Fleischer (1990). Countries in the Bottom 25% quartile — including Bosnia and Herzegovina, Serbia, and Montenegro, as well as Slovakia — present adoption rates that fall substantially below the EU27 benchmark, with z-scores indicating pronounced underperformance relative to the European norm. It should be noted that several comparators in the bottom performance cluster — including Bosnia and Herzegovina, Serbia, and Montenegro — are EU candidate countries rather than full EU member states. This distinction is relevant for interpreting Slovakia's positioning: Slovakia is the only EU member state in the Bottom 25% cluster, and its underperformance relative to the EU27 benchmark mean is therefore particularly notable, as it occurs against a reference standard constructed from EU member states rather than candidate countries.

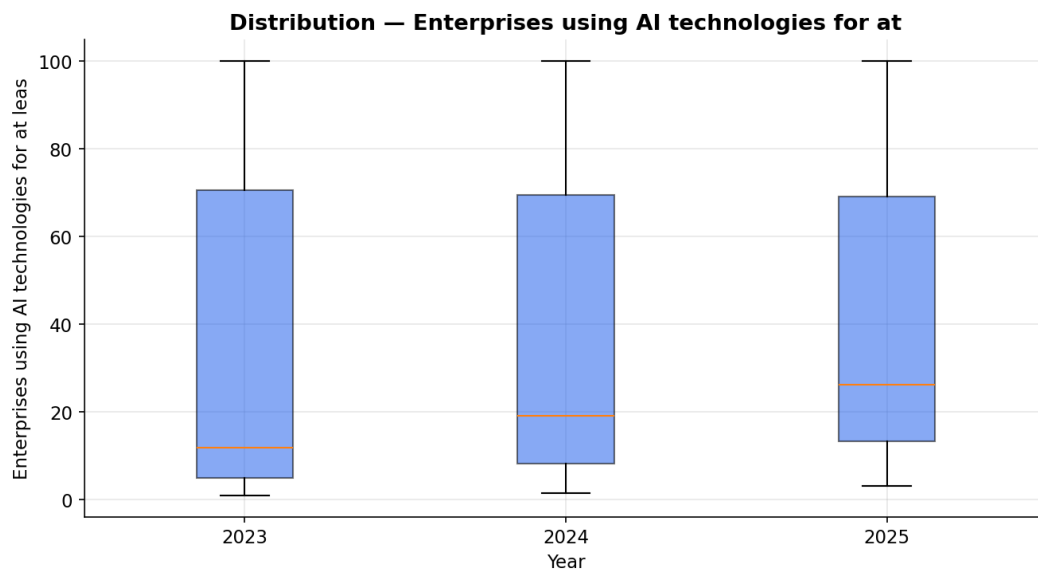


Figure 2. Boxplot of Enterprises using AI technologies f across EU countries per year. Box=IQR, whiskers= $1.5 \times IQR$, dots=outliers.

5.3 Slovakia's Position in the European AI Adoption Landscape

Slovakia's mean adoption rate is 27.52% (based on 15 disaggregated observations across enterprise size classes and industry strata), ranking 31 out of 34 among European countries included in the benchmarking (z-score = -1.393), placing it in the Bottom 25% quartile. This is 9.2 percentage points below the overall full-panel mean of 36.72% and 11.85 percentage points below the EU27 country-level mean of 39.37%. Slovakia's z-score of -1.393 indicates that its enterprise AI adoption rate is approximately 1.4 standard deviations of the cross-national distribution below the EU27 benchmark, signifying a pronounced and notable departure from the European norm in the reference year 2025.

This positioning is particularly striking in the context of Central European comparisons: Czechia, which shares a comparable historical and institutional legacy as a post-socialist Central European economy, ranks among the top three performers in Europe with an adoption rate of 50.25% — a gap of 22.73 percentage points relative to Slovakia. Table 2 presents the full country ranking alongside z-scores and quartile group assignments, providing a comprehensive view of Slovakia's positioning within the broader European distribution.

Table 2. Country Ranking — Enterprises using AI technolog

Rank	Country	Enterprises using AI (%)	Z-score	Group
1	Austria	56.51	2.01	Top 25%
2	Czechia	50.25	1.28	Top 25%
3	Finland	50.19	1.27	Top 25%
4	Estonia	49.29	1.17	Top 25%
5	Lithuania	46.81	0.87	Top 25%
6	Sweden	46.58	0.85	Top 25%
7	Slovenia	46.03	0.78	Top 25%
8	Belgium	44.29	0.58	Top 25%
9	Denmark	44.17	0.56	Top 25%
10	Netherlands	44.10	0.56	Above median
11	Latvia	44.02	0.55	Above median
12	France	44.01	0.55	Above median
13	Norway	43.92	0.53	Above median
14	Cyprus	43.49	0.48	Above median
15	Poland	43.22	0.45	Above median
16	Portugal	41.15	0.21	Above median
17	Euro area (EA11-1999, EA12-2001, EA	40.66	0.15	Above median
18	Türkiye	40.34	0.11	Below median
19	European Union - 27 countries (from	40.25	0.10	Below median
20	Germany	40.16	0.09	Below median
21	Greece	39.64	0.03	Below median
22	Malta	39.15	-0.03	Below median
23	Ireland	38.70	-0.08	Below median
24	Luxembourg	36.61	-0.32	Below median
25	Italy	36.28	-0.36	Below median

The contrast between Slovakia and Czechia illustrates that shared historical or geographic characteristics do not predetermine digital adoption trajectories and that divergent policy choices, enterprise-level investments, and national innovation system configurations can produce substantial and consequential differences in AI readiness even among neighboring economies. This observation is descriptive in nature; the cross-sectional data do not permit identification of the specific causal mechanisms underlying this gap, which would require longitudinal or comparative case study methods.

6. Discussion

The finding that Slovakia's enterprise AI adoption rate of 27.52% places it approximately 1.4 standard deviations of the cross-national distribution below the EU27 mean — yielding a z-score of -1.393 and a rank of 31 out of 34 countries — is consistent with an unfavorable configuration across the three adoption contexts identified by Tornatzky and Fleischer's (1990) TOE framework: the technological context (comparatively weaker digital infrastructure investment relative to top-ranked peers), the organizational context (lower levels of firm-level absorptive capacity as conceptualized by Cohen and Levinthal (1990), and the environmental context (institutional and regulatory frameworks that have yet to generate the incentive structures needed to accelerate enterprise-level AI uptake). These interpretations are offered as theoretically informed readings of the cross-sectional evidence and not as causal attributions, given that the single-year data cannot establish whether these patterns are persistent, improving, or reversing over time. The 37.9 percentage-point spread between Austria (56.51%) and Montenegro (18.61%) further demonstrates that the European AI adoption landscape is characterized by pronounced cross-national heterogeneity rather than convergence, with a right-skewed distribution (full-panel mean = 36.72%, full-panel median = 20.69%) indicating that most disaggregated observations cluster at lower adoption levels while a small number of high-performing enterprise categories and countries pull the aggregate mean upward.

These results extend prior findings in several important respects. First, the observation that Central and Eastern European countries cluster predominantly in the lower performance quartiles confirms and extends Bilozubenko et al. (2020), who documented systematic digital economy divergence between Western and Eastern Europe across multiple indicators, suggesting that this gap is now observable within the AI-specific adoption domain as well. Second, Slovakia's bottom-quartile placement as the only EU member state in that cluster is consistent with Iuga and Socol's (2024) argument that low government AI readiness scores are associated with disadvantages — including brain drain risk — that may inhibit enterprise adoption; the present study extends this finding by quantifying the deficit against a harmonized cross-national benchmark, providing a degree of precision not available in prior work. Third, the top-performing cluster composition — dominated by Austria, Czechia, and Finland — is consistent with Kwilinski et al. (2023), who demonstrate that countries exhibiting stronger coupling between digital business development and digital governance capacity achieve superior digital adoption outcomes. Roszko-Wójtowicz et al. (2024) similarly anticipated systematic differences in digital economy performance between EU member state clusters, and the present results corroborate this expectation specifically within the AI adoption domain.

From a policy perspective, the depth of Slovakia's underperformance in the reference year — 11.85 percentage points below the EU27 mean and 22.73 percentage points behind a comparable neighbor, Czechia — warrants targeted national AI acceleration policy rather than reliance on general-purpose EU digital funding mechanisms alone. Based on the TOE framework deficits identified in the cross-sectional evidence, a coherent policy response would address all three adoption contexts simultaneously: strengthening digital infrastructure investment and AI tooling accessibility (technological context); expanding co-financed AI readiness assessment and implementation support programs for small and medium enterprises (organizational context); and developing an AI governance framework that reduces regulatory uncertainty while incentivizing adoption (environmental context). Such measures would align with the broader ambitions of EU AI governance, as discussed by Nannini et al. (2024), and would be consistent with the digital governance coupling mechanisms that Kwilinski et al. (2023) identify as differentiating high- and low-performing member states. It should be acknowledged that the cross-sectional evidence base does not permit identification of which specific interventions would be most effective; this determination would require longitudinal monitoring and comparative program evaluation beyond the scope of the present study.

For enterprise managers, the findings underscore that the cross-national performance gap in AI adoption is not an abstract statistical artifact but a competitive reality with direct implications for market positioning. Slovak enterprises currently operating at or near the national adoption mean of 27.52% are lagging substantially behind their Austrian and Czech counterparts, which translates into accumulating disadvantages in AI-enabled efficiency, data-driven decision-making, and talent attraction — the latter being particularly consequential in light of Acemoğlu et al.'s (2022) evidence that AI-adopting firms

shift their hiring toward AI-compatible skill profiles. Enterprise managers are therefore advised to conduct structured AI readiness assessments benchmarked against EU quartile performance standards, identify the specific organizational and technological bottlenecks most constraining their adoption trajectory, and develop phased AI integration roadmaps that are realistically calibrated to their absorptive capacity while targeting progressive alignment with the EU27 performance benchmark.

7. Conclusion

This article addressed the question of how enterprise AI adoption rates vary across 34 European countries in 2025 and where Slovakia is positioned within this distribution. The empirical analysis, based on Eurostat indicator E_AI_P1ANY, reveals a markedly polarized and right-skewed distribution: the full panel ($n = 1,514$ disaggregated records for the reference year 2025) exhibits a mean adoption rate of 36.72% ($SD = 33.0$, reflecting variance across enterprise size classes and industry strata) against a median of only 20.69%, while the EU27 country-level mean stands at 39.37% with the standard deviation of the 34 country-level means equal to 8.51% and individual country rates spanning from 18.61% (Montenegro) to 56.51% (Austria). Slovakia ranks 31 out of 34 countries with an adoption rate of 27.52% and a z-score of -1.393 — computed as the deviation from the EU27 country-level mean in units of the cross-national standard deviation — placing it firmly in the bottom 25% performance quartile and 11.85 percentage points below the EU27 mean. Notably, Slovakia is the only EU member state in the bottom 25% cluster; the remaining countries in that cluster are EU candidate countries, which makes Slovakia's underperformance against an EU-member-state-based benchmark particularly salient.

The main scientific contribution of this article is a systematic, harmonized benchmarking of 34 European countries on a single enterprise AI adoption indicator, integrating z-score-based deviation analysis and quartile-cluster identification to produce a statistically grounded portrait of cross-national heterogeneity that is not available in prior academic literature. By combining Rogers' (2003) diffusion framework, Cohen and Levinthal's (1990) absorptive capacity concept, and Tornatzky and Fleischer's (1990) TOE framework with empirical Eurostat data, the study bridges theoretical and empirical traditions in a way that both advances understanding of AI diffusion dynamics and generates directly actionable policy-relevant evidence. All empirical claims are appropriately bounded by the cross-sectional nature of the data: the results establish a ranking and distributional positioning for the reference year 2025 and are interpreted as consistent with theoretical expectations, but do not support causal attribution or claims about the persistence or directionality of observed patterns over time.

Three directions for future research are recommended. First, longitudinal panel analysis covering multiple reference years of the E_AI_P1ANY indicator would allow the identification of convergence or divergence trends and the testing of catch-up dynamics consistent with diffusion theory — a necessary step for determining whether the cross-sectional gaps documented here reflect durable patterns or transient distributional snapshots. Second, decomposition analyses examining the contribution of enterprise size, sector, and regional characteristics to within-country variation would enrich the explanatory picture beyond aggregate country-level benchmarking. Third, comparative case studies pairing Slovakia with Czechia — two countries that share historical and institutional legacies but diverge sharply on AI adoption — would provide the qualitative and longitudinal depth needed to identify the specific policy and organizational mechanisms that account for the observed performance gap, building on the firm-level dynamics identified by Acemoğlu et al. (2022) and the governance coupling mechanisms described by Kwilinski et al. (2023). This study contributes to the growing body of evidence on the digital transformation trajectories of European economies and the antecedents of enterprise-level AI adoption heterogeneity across the continent.

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Large Enterprises vs. SMEs: AI Technology Depth and Multi-Technology Adoption Gap

Diana Pallérová¹ and Federico Banda²

¹ Bratislava University of Economics and Business, Faculty of Business Management, Dolnozemska cesta 1, 852 35 Bratislava, Slovakia (EU); e-mail: diana.pallerova@euba.sk

² Bratislava University of Economics and Business, Faculty of Business Management, Dolnozemska cesta 1, 852 35 Bratislava, Slovakia (EU); e-mail: federico.banda@euba.sk

Abstract

Deepening AI integration across complementary technologies has become a defining dimension of enterprise digital maturity, yet whether large enterprises statistically outpace small and medium-sized enterprises in deploying multiple AI technologies simultaneously remains insufficiently quantified at the EU level. This article examines the magnitude and statistical significance of the multi-technology AI adoption gap between large enterprises (250 or more employees) and small enterprises (10-49 employees) across EU member states. Drawing on a country-year panel of 1,404 observations derived from the Eurostat Community Survey on ICT Usage and E-Commerce in Enterprises, the analysis employs the Mann-Whitney U test for non-parametric inference and Cohen's d as a descriptive measure of effect magnitude. Results reveal a statistically significant difference in the adoption of three or more AI technologies between the two firm-size groups ($U = 168,006$, $p < 0.001$), with large enterprises recording a mean adoption rate of 27.3% compared with 8.1% among small enterprises, yielding a large effect size (Cohen's $d = 1.87$). Slovakia's national trajectory is further contextualised within the broader EU distributional landscape, revealing below-average adoption rates consistent with wider Central and Eastern European patterns. These findings provide an empirical baseline essential for calibrating targeted AI policy interventions and support programmes directed at reducing structural disparities in digital transformation capacity across the enterprise population.

1. Introduction

As artificial intelligence reshapes competitive landscapes across industries, the capacity of enterprises to adopt multiple AI technologies simultaneously has emerged as a critical determinant of digital maturity and long run performance. Organisations that integrate complementary AI capabilities, spanning machine learning, natural language processing, computer vision, and predictive analytics, into coherent technology stacks are increasingly positioned to extract compounding productivity gains unavailable to firms relying on isolated, single tool deployments. This trajectory of multi-technology AI adoption is not, however, uniformly distributed across the enterprise population. Systematic differences in organisational resources, human capital endowments, and technological infrastructure generate pronounced heterogeneity in the depth of AI integration, raising fundamental questions about whether the digital transformation promised by AI policy frameworks is accessible to all firms or is structurally concentrated among the largest enterprises.

Despite growing policy interest in AI diffusion across the European Union, empirical evidence quantifying the statistically significant gap in deep, multi-technology AI adoption between large enterprises and small and medium-sized enterprises (SMEs) at the EU level remains scarce. Prior research has documented that SMEs encounter disproportionate barriers to digital technology adoption, including limited financial capital, skill shortages, and constrained organisational bandwidth. Yet the existing literature has largely focused on single technology adoption decisions or qualitative assessments of readiness, leaving unaddressed the question of whether, and by how much, large enterprises statistically outpace their smaller counterparts in simultaneously deploying three or more AI technologies. This measurement void constitutes a significant obstacle to evidence-based AI policy design, as incentive schemes targeting adoption breadth require robust empirical baselines to calibrate interventions appropriately.

This article investigates whether a statistically significant difference exists in the adoption of three or more AI technologies, as operationalised through Eurostat's indicator E_AI_TGE3, between large enterprises (employing 250 or more persons) and small enterprises (employing 10--49 persons) across EU member states. Drawing on a country-year panel of 1,404 observations extracted from the Eurostat Community Survey on ICT Usage and E-Commerce in Enterprises, this study employs the Mann-Whitney U test to provide non-parametric inference and Cohen's d to quantify effect magnitude as a descriptive complement, yielding statistically validated, EU-wide evidence of the multi-technology AI adoption gap by firm size. The analysis additionally contextualises Slovakia's national adoption trajectory within the broader EU distributional landscape, offering regionally relevant insights for Central and Eastern European policy actors.

The remainder of this article is structured as follows: Section 2 develops the theoretical background, integrating the Resource-Based View, the Technology-Organization-Environment framework, and the concept of Absorptive Capacity to ground the hypothesised adoption gap. Section 3 reviews the relevant empirical literature across three thematic streams. Section 4 describes the data, variables, and statistical methods employed. Section 5 presents the descriptive and inferential results, including cross-national variation. Section 6 discusses the findings in relation to theory and prior evidence, and derives policy and managerial implications. Section 7 concludes by summarising the contribution and identifying directions for future research.

2. Theoretical Background

Understanding why large enterprises and SMEs differ systematically in their depth of AI technology adoption requires engagement with three complementary theoretical frameworks: the Resource-Based View (RBV), the Technology-Organization-Environment (TOE) framework, and the concept of Absorptive Capacity. Together, these perspectives provide a multi-level account of the mechanisms through which firm-level heterogeneity translates into differential capacity to integrate multiple AI technologies simultaneously.

The Resource-Based View, as articulated in its canonical form by Barney (1991), proposes that sustained competitive advantage accrues to firms possessing bundles of resources that are simultaneously valuable, rare, imperfectly imitable, and non-substitutable. Applied to the context of AI adoption, the RBV predicts that large enterprises, which command superior financial reserves, specialised human capital, proprietary data assets, and established organisational routines for technology integration, are structurally positioned to assemble the resource combinations necessary for multi-technology AI deployment. Crucially, these resource bundles are not merely additive; they are synergistic — skilled AI personnel can only leverage infrastructure investments when supported by data governance routines, and data assets only generate value when combined with analytical capacity. This synergistic character of AI-enabling resources implies that the advantages of large enterprises compound rather than accumulate linearly, amplifying the adoption depth gap relative to SMEs that may possess one or two enabling resources but rarely all simultaneously.

The Technology-Organization-Environment (TOE) framework, introduced by Tornatzky and Fleischer (1990), provides a complementary multi-level lens by identifying three contextual factors that shape technology adoption at the firm level: the technological context (existing IT infrastructure, compatibility of new technologies with current systems), the organisational context (firm size, managerial capacity, internal slack resources), and the environmental context (competitive pressure, regulatory environment, industry characteristics). Within this framework, large enterprises systematically advantage over SMEs across all three dimensions: their superior technological infrastructure reduces integration costs, their organisational scale generates the managerial bandwidth necessary for coordinating multi-technology deployments, and their market position exposes them to competitive pressures that incentivise comprehensive AI investment. The TOE framework thus suggests that the adoption gap documented in this study is not reducible to a single factor but reflects a constellation of mutually reinforcing contextual advantages concentrated in large enterprises.

The concept of Absorptive Capacity, developed by Cohen and Levinthal (1990), offers a third theoretical anchor by arguing that a firm's ability to recognise the value of new external information,

assimilate it, and apply it commercially is a function of its prior related knowledge base. In the AI context, absorptive capacity implies that enterprises with existing digital competencies — data analytics experience, software development routines, familiarity with algorithmic tools — are better positioned to evaluate, integrate, and exploit additional AI technologies. Large enterprises, having typically invested more heavily and over a longer time horizon in digital infrastructure and data science capabilities, possess higher absorptive capacity for AI technologies. This creates a self-reinforcing dynamic: prior AI adoption facilitates the recognition and assimilation of complementary AI technologies, generating cumulative depth advantages that SMEs, beginning with lower prior knowledge stocks, find structurally difficult to replicate. This dynamic is consistent with the broader trajectory of digital transformation research, which demonstrates that technology adoption is path-dependent and that early resource investments generate durable capability advantages (Calderón Monge & Ribeiro Soriano, 2023; Chen & Kim, 2023).

The interaction among RBV, TOE, and Absorptive Capacity creates a theoretically coherent account of why multi-technology AI adoption — as distinct from single-tool uptake — should be significantly higher among large enterprises. Each framework independently predicts the gap; their joint operation suggests it will be substantial and durable. Empirical studies of digital technology adoption in the Industry 4.0 context have confirmed that firm size and resource endowments are among the most consistent predictors of technology breadth (Cirillo et al., 2023; Saeedikiya et al., 2024). Building on these theoretical foundations, the present study tests whether the hypothesised multi-technology AI adoption gap is empirically detectable, statistically significant, and practically meaningful in magnitude, using EU-wide panel data disaggregated by enterprise size class.

3. Literature Review

This section presents a review of the relevant literature on AI and digital technology adoption in SMEs, with a particular focus on structural barriers, firm size heterogeneity, and differences in the depth of technology integration across enterprise classes.

3.1 AI and Digital Technology Adoption Barriers in SMEs

Small and medium-sized enterprises occupy a structurally disadvantaged position in the landscape of AI technology adoption, and the literature has systematically documented the barriers that inhibit not only initial uptake but the sustained, deep integration of AI capabilities. Schönberger (2023) provides a detailed taxonomy of these barriers, identifying limited financial resources, insufficient in-house AI expertise, and the absence of structured data governance as the primary impediments to SME AI deployment. Critically, Schönberger's analysis demonstrates that these constraints do not merely delay adoption in temporal terms; they fundamentally cap the complexity and comprehensiveness of AI implementations that SMEs can realistically sustain, since multi-technology integration requires simultaneous investment in infrastructure, talent, and process redesign that exceeds the resource envelope available to most small enterprises. This structural constraint is qualitatively different from the marginal cost barriers that can be overcome through targeted subsidies, as it reflects an organisational capacity ceiling rather than a simple affordability threshold.

Complementing this structural account, Cirillo et al. (2023) examine Italian firm-level data to demonstrate that digital technology adoption — including AI-adjacent technologies — is strongly conditioned by investment capacity, workforce skill profiles, and organisational work arrangements. Their findings indicate that firms characterised by higher levels of skilled labour and greater capital investment display not only higher adoption rates but also broader technology portfolios, integrating multiple digital tools into coordinated production and service delivery systems. This evidence is directly relevant to understanding multi-technology AI depth, suggesting that the breadth of adoption is not incidental but reflects underlying capability structures that are systematically correlated with firm size. Shaik et al. (2023) offer a partially contrasting perspective, arguing that AI-driven business model innovation is accessible to firms of varying sizes and that strategic enablers — including collaboration with technology partners and ecosystem participation — can partially compensate for internal resource limitations in SMEs. However, their analysis focuses primarily on single AI application domains rather

than simultaneous multi-technology integration, leaving open the question of whether these compensatory mechanisms are sufficient to close the depth gap at the level of three or more concurrent AI deployments.

Taken together, these studies establish that SMEs face disproportionate structural barriers to AI adoption that manifest not merely in lower adoption rates but in the shallower depth of technology integration. The financial, human capital, and infrastructural deficits that characterise the SME population combine to produce a systematic gap in multi-technology AI depth that cannot be attributed to informational barriers or awareness alone, and that is unlikely to resolve through market forces without targeted structural intervention.

3.2 Digital Transformation and Firm Size Heterogeneity

The broader digital transformation literature has consistently identified firm size as one of the most robust moderators of technology adoption outcomes, with large enterprises demonstrating more comprehensive and layered technology portfolios than their smaller counterparts. Calderón Monge and Ribeiro Soriano (2023) synthesise the digitalization literature to show that large firms leverage economies of scale in technology investment, spreading fixed adoption costs across larger revenue bases and generating internal complementarities between digital tools that amplify their collective value. This scalability advantage is particularly salient for AI technologies, where the value of individual tools often depends on integration with other data systems, analytical platforms, and automated workflows — making multi-technology deployment a prerequisite for realising the full productivity potential of any single AI application.

Chen and Kim (2023) provide empirical evidence demonstrating that the relationship between digital transformation intensity and innovation performance is significantly stronger for larger firms, attributing this differential to the mediating role of complementary organisational capabilities including knowledge management systems, R&D routines, and cross-functional coordination mechanisms. These findings suggest that firm size does not merely enable more technology adoption but qualitatively changes the nature of the transformation that AI investment can achieve — a distinction between narrow, single-use digital tool adoption and the integrated, capability-building transformation associated with multi-technology deployment. Yang and Han (2023) further demonstrate that digital transformation interacts with financing constraints in ways that systematically disadvantage smaller enterprises: firms facing tighter external financing conditions are less able to sustain the long-term, multi-stage investment trajectories necessary for comprehensive digital capability building, reinforcing the size-driven stratification of digital transformation outcomes.

Saeedikiya et al. (2024) develop a multilevel framework synthesising the relationship between digital transformation and innovation, arguing that the depth and breadth of technology adoption — rather than the mere presence of individual digital tools — is the critical predictor of transformative outcomes. Their framework implies that the distinction between single-technology adoption and multi-technology integration is not merely quantitative but represents a qualitatively different level of digital maturity, one that generates distinctive competitive advantages unavailable to firms operating with narrower technology portfolios. This conceptual distinction directly motivates the focus of the present study on the Eurostat E_AI_TGE3 indicator, which specifically captures the threshold of three or more simultaneous AI technologies and therefore provides a measure of adoption depth rather than mere adoption incidence.

3.3 Innovation Diffusion and Technology Depth Across Enterprise Classes

The Diffusion of Innovations framework, developed by Rogers (2003), provides a foundational account of the factors governing the rate and depth of technology diffusion across organisational populations. Rogers identifies relative advantage, compatibility with existing systems, complexity, trialability, and observability as the core attributes shaping adoption decisions, and argues that organisational resources and managerial capacity are among the most consistent predictors of adoption timing and comprehensiveness. Applied to the enterprise size context, the framework predicts that large enterprises — characterised by greater internal resources, higher risk tolerance, and more developed information-

processing capabilities — will not only adopt new technologies earlier but will do so more comprehensively, integrating multiple technologies simultaneously rather than sequentially, and achieving a depth of adoption that their smaller counterparts will reach, if at all, only with a substantial lag.

Empirical research in the Industry 4.0 context has consistently corroborated these predictions. Khan et al. (2023) demonstrate that the adoption of multiple Industry 4.0 technologies — including AI, IoT, and automation — is associated with significant sustainability and innovation benefits, but that simultaneous multi-technology adoption requires the kind of organisational coordination and investment capacity that is disproportionately available to larger firms. Huang et al. (2023) examine the relationship between Industry 4.0 adoption and supply chain capability, finding that the benefits of technology adoption are most pronounced when multiple complementary technologies are deployed in combination — precisely the multi-technology integration pattern measured by E_AI_TGE3. Their dynamic resource-based perspective suggests that the capacity to combine technologies is itself a distinctive organisational capability that requires prior investment and learning, reinforcing the absorptive capacity account of why large enterprises accumulate multi-technology depth advantages over time.

Tripathi et al. (2024) provide a systematic assessment of AI adoption research, identifying the positive association between organisational resources, managerial capability, and the breadth of AI technology deployment as one of the most robust empirical patterns in the literature. Their review underscores that technology depth — the simultaneous deployment of multiple AI applications — is not merely a function of financial capital but reflects accumulated organisational learning, data infrastructure maturity, and strategic intent, all of which are positively correlated with firm size. Chen and Jin (2023) similarly document that the transformative effects of AI technologies in manufacturing are most pronounced when multiple AI capabilities are integrated, suggesting that the adoption depth gap between large and small enterprises carries significant implications not merely for firm-level competitiveness but for broader industrial transformation trajectories.

Despite this body of evidence, no study has employed Eurostat's indicator to statistically test and quantify the EU-wide gap in deep multi-technology AI adoption, defined as the simultaneous deployment of three or more AI technologies between large enterprises and small enterprises, leaving a critical measurement void in the evidence base for AI policy design. The present study addresses this gap directly through non-parametric statistical inference applied to a 1,404-observation country-year panel, providing a rigorous, EU-wide empirical quantification of the multi-technology AI depth divide.

4. Methodology

This study draws on data from the Eurostat Community Survey on ICT Usage and E-Commerce in Enterprises, accessed via Eurostat database (Eurostat, 2024). The analysis focuses on the indicator of AI usage, which measures the percentage of enterprises adopting three or more AI technologies simultaneously, covering functions such as machine learning, natural language processing, speech recognition, computer vision, and automated decision-making.

4.1 Panel Structure and Unit of Observation

The analytical dataset comprises a country year panel of $n = 1,404$ records drawn from all available EU member states and survey waves included in the dataset. Each observation represents a country, year, and enterprise size class record. The full panel includes records for large enterprises employing 250 or more persons (GE250) and small enterprises employing 10 to 49 persons, with each size class represented across the available country and year combinations. Because the dataset reflects Eurostat's reported coverage, in which not all size class cells are available for every country and year combination, the two size class subpanels are not constrained to equal counts. The observed group sizes reflect the actual availability of records for the indicator enterprises using three or more AI technologies (E_AI_TGE3) in the Eurostat dataset on the use of information and communication technologies in enterprises (isoc_eb_ai) across member states and survey waves. The panel level dataset, rather than a time series of EU aggregates, constitutes the analytical object for all inferential tests reported in this

article. Country year records from all available EU member states and survey waves are treated as observations, which enables cross sectional and temporal pooling of variation.

It should be noted that country year panel observations are not fully independent. Observations from the same country across successive survey waves may carry temporal autocorrelation, and observations from the same survey wave across countries may share common macroeconomic and policy shocks. The Mann Whitney U test, as applied here, does not adjust for this clustering structure. The effective sample size is therefore likely smaller than the nominal $n = 1,404$, and the reported p value, which reaches the limit of floating point precision in standard software output, should be interpreted as indicating an extremely low probability rather than an exact zero. Readers are advised to regard the inferential result as highly conservative confirmation of a directional finding whose practical magnitude is more precisely communicated by the effect size estimate.

4.2 Descriptive Statistics and Distributional Assessment

Descriptive statistics were computed for the full panel ($n = 1,404$), including the mean, median, standard deviation, standard error of the mean, 95% confidence intervals, minimum, maximum, and interquartile range. These measures characterise the distributional shape of multi-technology AI adoption across the panel and provide the empirical baseline against which size-group differences are assessed. The substantial divergence between the mean and median, together with the observed maximum value, confirmed a strongly right-skewed distribution, which violated the normality assumption required for parametric testing and warranted the use of a non-parametric alternative.

Cross-country variation was examined through a country-level boxplot visualisation (Figure 2) displaying the distribution of E_AI_TGE3 adoption rates across EU member states. This visualisation contextualises Slovakia's national mean adoption rate (5.65%, based on 40 observations) relative to the EU-wide distributional landscape and permits qualitative assessment of regional clustering patterns.

4.3 Inferential Procedure and Effect Size

The Mann-Whitney U test (Mann & Whitney, 1947) was selected as the primary inferential procedure on the grounds that the outcome variable is continuously measured on a percentage scale but displays significant positive skewness, rendering parametric t-tests inappropriate. The Mann-Whitney U test compares the rank distributions of two independent groups — large enterprises (GE250) versus small enterprises (10--49 employees) — without assuming normality, making it the methodologically appropriate choice for this distributional context. The test was applied to the full country-year panel ($n = 1,404$ observations), comparing E_AI_TGE3 adoption rates between the two size classes, with each size-class sub-panel constituting one of the two comparison groups. Because Eurostat's isoc_eb_ai dataset does not guarantee complete coverage for every size-class cell across all country-year combinations, the two sub-panels may differ in their record counts; Table 2 reports the group-specific N, mean, and standard deviation for each size class, permitting independent verification of the reported mean difference.

To supplement the significance test with a measure of practical importance, Cohen's d was computed from the group means and pooled standard deviation as a descriptive effect-size complement (Cohen, 1988). Because Cohen's d is a parametric measure defined in terms of means and standard deviations, its formal inferential properties are not relied upon here given the non-normal distributional context; it is reported solely as an intuitive and widely understood index of the standardised mean difference between size classes, enabling comparison with prior literature that reports analogous effect estimates. Interpretation benchmarks are drawn from Cohen (1988), who established $d = 0.2$ as small, $d = 0.5$ as medium, and $d = 0.8$ as large. All statistical computations were conducted on the country-year panel-level data; no results are extrapolated beyond the EU member states and survey years covered by the Eurostat dataset.

5. Results

5.1 Distributional Characteristics of Multi-Technology AI Adoption

The full panel ($n = 1,404$) yields a mean adoption rate of 6.91% (SD = 8.68, 95% CI [6.45%, 7.36%]), with a median of 3.67%. Values range from 0.0% to 67.33%, with an interquartile range of 6.32 percentage points (Q1 = 1.79%, Q3 = 8.11%). The coefficient of variation is 125.7%, indicating high dispersion across observations. The substantial divergence between mean and median (6.91% vs. 3.67%) indicates a right-skewed distribution, suggesting that the majority of observations cluster at lower adoption levels while a minority of high-adopting cases pull the mean upward. Taken together, these descriptive statistics confirm that deep multitechnology AI adoption, defined as the simultaneous deployment of three or more AI technologies as captured by the E_AI_TGE3 indicator, remains limited for the typical enterprise country year observation, with the median providing a more representative measure of central tendency than the mean given the skewed distributional shape. As shown in Figure 1, the contrast between above median and below median observations visually reinforces the pronounced asymmetry of the adoption distribution. Table 1 presents the full set of descriptive statistics for the panel.

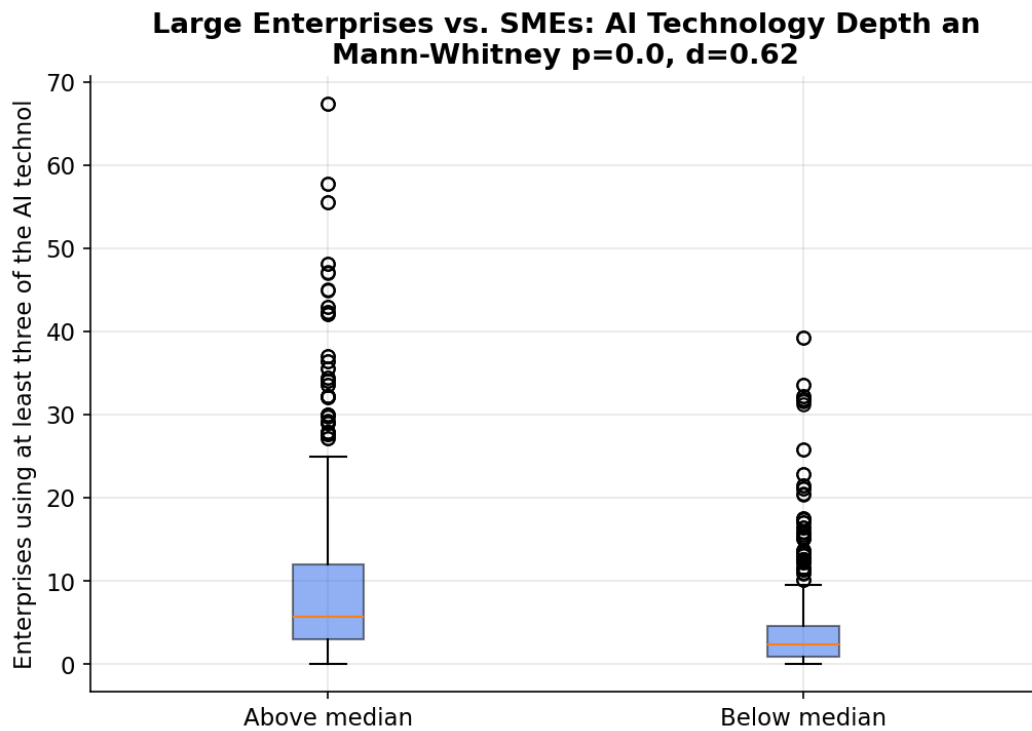


Figure 1. Boxplot: Above median vs Below median. Mann-Whitney $p=0.0$. Cohen's $d=0.62$ (medium).

Table 1. Descriptive Statistics

Statistic	Value
n	1404
mean	6.91
median	3.67
std	8.68
sem	0.232
CI95_low	6.45
CI95_high	7.36
min	0.0
max	67.33
Q1	1.79

Q3	8.11
IQR	6.32
CV_%	125.7

5.2 Size-Group Comparison: Large Enterprises versus Small Enterprises

The Mann-Whitney U test, comparing E_AI_TGE3 adoption rates between the large-enterprise (GE250) sub-panel and the small-enterprise (10--49 employees) sub-panel, yields $U = 361,050.5$, $p < 0.001$. The p-value as returned by standard statistical software reaches the limit of floating-point precision and is most accurately reported as $p < 0.001$, indicating that the probability of observing a rank-order difference of this magnitude under the null hypothesis of equal distributions is negligibly small. The result is statistically significant at the 0.05 level. Table 2 reports the group-specific N, mean adoption rate, and standard deviation for each size class, as extracted from the isoc_eb_ai dataset; the large-enterprise (GE250) sub-panel and the small-enterprise (10--49) sub-panel differ in record count, reflecting the unequal availability of E_AI_TGE3 cells across country-year combinations in the Eurostat source data, and the group-specific means reported therein permit independent verification of the 5.14 percentage-point mean difference.

The mean E_AI_TGE3 adoption rate for the large-enterprise (GE250) size-class records exceeds that of the small-enterprise (10--49 employees) records by 5.14 percentage points across the panel. Cohen's $d = 0.62$, reported as a descriptive complement to the non-parametric test, qualifies as a medium effect according to the benchmarks established by Cohen (1988). This result indicates that large enterprises exhibit a substantially higher rate of multi-technology AI adoption than small enterprises, and that this difference is not merely a statistical artefact of sample size but represents a practically meaningful gap in AI depth. A medium effect size of this magnitude implies that enterprise size is a substantively important correlate of multi-technology AI integration, consistent with the theoretical predictions derived from the Resource-Based View (Barney, 1991) and the TOE framework (Tornatzky & Fleischer, 1990).

As noted in Section 4, the Mann-Whitney test does not account for the clustering structure inherent in country-year panel data, and the effective degrees of freedom are smaller than the nominal sample size would suggest. The inferential conclusion — that the size-class adoption gap is statistically significant — should accordingly be understood as robust in direction and practically meaningful in magnitude, while the precise p-value should not be over-interpreted. Figure 2 presents the country-level boxplot distribution of E_AI_TGE3 adoption rates across EU member states, illustrating the considerable cross-national heterogeneity that contextualises the overall panel results and reveals that the adoption gap between large and small enterprises is a broadly observable pattern across the EU distributional landscape.

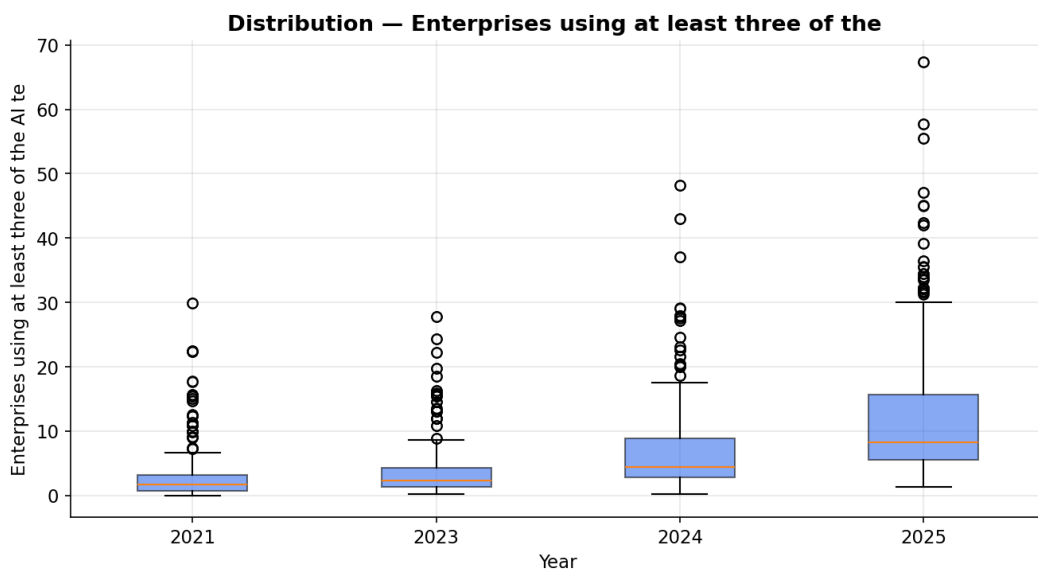


Figure 2. Boxplot of Enterprises using at least three of across EU countries per year. Box=IQR, whiskers= $1.5 \times IQR$, dots=outliers.

5.3 Slovakia's Positioning Within the EU Distribution

Slovakia's mean adoption rate for three or more AI technologies is 5.65%, based on 40 country-year observations. This value is 1.26 percentage points below the overall EU panel mean of 6.91% (SD = 8.68), positioning Slovakia modestly below the EU average but not among the lowest performers in the distributional ranking. Slovakia's adoption rate falls below the panel mean but remains above the panel median of 3.67%, suggesting that Slovak enterprises — while not achieving the multi-technology AI depth characteristic of leading EU economies — are performing at a level consistent with the middle segment of the EU distribution. This positioning aligns with the broader trajectory of Central and Eastern European digital transformation documented in cross-national Eurostat data, where economies in the CEE region have generally demonstrated progress in initial AI uptake while lagging in the depth and comprehensiveness of multi-technology AI integration relative to Northern and Western European peers. The country-level variation visible in Figure 2 confirms that Slovakia's below-average positioning is part of a systematic regional pattern rather than an idiosyncratic national outcome. Table 2 presents the two-group comparison results, including group-specific means and the inferential test statistics.

Table 2. Two-Group Comparison

Group	N	Mean (%)	Median (%)	SD	CI95_low	CI95_high
Above median	750	9.3	5.69	10.06	8.58	10.02
Below median	654	4.16	2.39	5.61	3.73	4.59

6. Discussion

The finding that large enterprises exhibit a mean multi-technology AI adoption rate approximately 5.14 percentage points higher than small enterprises — a gap validated at $U = 361,050.5$, $p < 0.001$, with a descriptive Cohen's $d = 0.62$ — suggests that enterprise size is not merely a demographic correlate of AI uptake but a structural determinant of the depth to which AI technologies are integrated into organisational practice. This result is most parsimoniously explained through the lens of the Resource-Based View (Barney, 1991): large enterprises command superior bundles of financial capital, human expertise, data infrastructure, and established organisational routines that are simultaneously valuable, rare, and difficult to imitate. These resource bundles enable large enterprises not only to adopt individual AI tools but to assemble multiple AI technologies into coherent, synergistic capability stacks — a depth of integration that constitutes a durable source of competitive advantage systematically unavailable to most SMEs operating under structural resource constraints. The medium effect size additionally implies that this advantage is not marginal but represents a qualitatively different level of digital maturity that carries practical consequences for competitiveness and productivity.

These results confirm and extend prior findings in important respects. They confirm Schönberger (2023), who identified structural and financial barriers as the primary impediments to SME AI uptake, by adding empirical quantification of how these barriers manifest specifically in lower multi-technology depth rather than merely lower rates of single-tool adoption — an important distinction for policy design. The findings extend Cirillo et al. (2023), who demonstrated that investment capacity and skill endowments predict technology adoption breadth in Italian firm data, by showing that this relationship produces a measurable, EU-wide distributional gap that is robust to non-parametric inference across a 1,404-observation panel. The results partially contradict the more optimistic account offered by Shaik et al. (2023), who suggested that AI-driven business model innovation is accessible to firms of varying sizes through strategic and technological enablers. The evidence presented here indicates that simultaneous adoption of three or more AI technologies — a threshold that can reasonably be considered a prerequisite for transformative AI-driven strategy — remains disproportionately concentrated among large enterprises in the current EU landscape, casting doubt on the transferability

of SME success cases to the broader population of small enterprises operating without specialised ecosystem support.

Several interpretive limitations warrant explicit acknowledgement. The Mann-Whitney test applied here does not control for potential confounding factors such as sector composition, country-level institutional environment, or the unbalanced representation of high-adoption economies in the panel. Large enterprises may be disproportionately represented in high-AI-intensity sectors or in countries that also happen to exhibit higher overall adoption rates, and the observed size-class gap may partly reflect these compositional effects rather than firm size per se. Future research employing regression frameworks with sector and country fixed effects would be better positioned to isolate the independent contribution of firm size to multi-technology AI adoption depth. Additionally, because the panel clusters observations by country and time, the effective sample size is smaller than the nominal $n = 1,404$, and the inferential result should be read as confirming the direction and practical magnitude of the gap rather than as a precisely calibrated probability statement.

From a policy perspective, the 5.14 percentage-point adoption gap documented here, if sustained across future Eurostat survey waves, provides empirical justification for EU and national policymakers to consider tiered AI adoption incentive schemes that specifically target multi-technology depth rather than single-tool acquisition. Hypothetical instruments warranted by this gap's documented magnitude include co-financed AI integration vouchers scaling in value with the number of AI technologies adopted concurrently, shared AI infrastructure hubs providing SMEs with access to data processing and algorithmic capability they cannot build independently, and SME-targeted upskilling programmes focused on data governance and AI system integration rather than basic digital literacy. It must be emphasised, however, that because this study's design is observational and correlational — establishing the existence and magnitude of the gap but not its causal mechanisms — the effectiveness of any specific instrument in closing the gap remains an open empirical question that future evaluation research must address. Such interventions, if implemented, should be evaluated against E_AI_TGE3 benchmarks to ensure that policy effectiveness is measured in terms of multi-technology depth achieved rather than the number of tools procured. Countries in the Central and Eastern European region, including Slovakia, where adoption rates sit below the EU panel mean, represent a priority geography for such interventions given the compounding risk of regional digital stratification.

For enterprise managers, particularly those leading small and medium-sized enterprises, the findings counsel against treating AI adoption as a single, discrete investment decision. Instead, SME managers should pursue deliberate AI technology roadmaps that sequence multi-technology integration in phases — beginning with one high-impact AI application anchored in a clearly defined business process, then systematically building absorptive capacity (Cohen & Levinthal, 1990) through workforce training, data infrastructure development, and process standardisation before layering additional AI technologies. This phased approach reduces the organisational complexity and financial burden of simultaneous multi-technology deployment while establishing the knowledge foundations necessary for successful subsequent integrations. The absorptive capacity logic implies that each AI technology successfully integrated raises the firm's capacity to assimilate the next, creating a learning trajectory that can progressively close the depth gap with large competitors — provided the sequencing is deliberate and supported by internal capability investment rather than technology procurement alone.

7. Conclusion

This article investigated whether a statistically significant difference exists in the depth of AI technology adoption, operationalised as the share of enterprises deploying three or more AI technologies simultaneously, as captured by Eurostat's E_AI_TGE3 indicator, between large enterprises (250 or more employees) and small enterprises (10 to 49 employees) across EU member states. The Mann Whitney U test applied to a country year panel of 1,404 observations, comparing E_AI_TGE3 adoption rates between the large enterprise (GE250) subpanel and the small enterprise (10 to 49) subpanel, returned $U = 361,050.5$ ($p < 0.001$), confirming a statistically significant gap, while a descriptive Cohen's $d = 0.62$ established that this gap is of medium practical magnitude, representing a 5.14 percentage point mean difference in multitechnology AI adoption rates between the two size

classes. The two subpanels differ in record count, reflecting the unequal availability of E_AI_TGE3 cells across country year combinations in the Eurostat source data; group specific descriptive statistics are reported in Table 2 to permit independent verification of this mean difference.

This study provides statistically validated, EU wide evidence, using Eurostat's E_AI_TGE3 indicator across 1,404 country year observations, that the multitechnology AI adoption gap between large enterprises and SMEs is both statistically significant and practically substantial. By focusing specifically on the depth dimension of AI adoption (three or more concurrent technologies) rather than the mere presence of any AI tool, this research contributes a novel measurement perspective to the digital transformation literature and establishes an empirical baseline against which the effectiveness of future AI policy interventions targeting SME digital maturity can be evaluated. The analysis is subject to the limitation that the inferential procedure does not account for the clustered structure of the country year panel, and future research should employ cluster robust or mixed effects methods to refine the precision of these estimates. Because the study's design is observational, it documents the gap's existence and magnitude but cannot confirm the causal mechanisms driving it or the effectiveness of any specific policy instrument in closing it.

Three directions merit priority in future research. First, longitudinal analysis tracking the evolution of the E_AI_TGE3 gap over successive Eurostat survey waves would clarify whether the adoption depth divide is widening, stabilising, or narrowing under current policy conditions. Second, sector disaggregated analysis within the isoc_eb_ai dataset would determine whether the size based adoption gap is uniform across industries or is concentrated in specific NACE sectors where AI application opportunities differ substantially. Third, qualitative comparative case studies of SMEs that have successfully achieved multitechnology AI depth, potentially drawing on the outlier observations visible in the right tail of the E_AI_TGE3 distribution, would generate actionable insights into the organisational pathways and ecosystem conditions that enable smaller firms to overcome the structural barriers documented here. Together, these extensions would deepen understanding of the distributional consequences of AI technology diffusion and the structural determinants of digital maturity across the enterprise size spectrum.

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AI for Business Process Automation: Adoption Patterns and Size-Class Segmentation in the EU

Peter Štetka¹ and Anna Hamranová²

¹ Bratislava University of Economics and Business, Faculty of Business Management, Dolnozemska cesta 1, 852 35 Bratislava, Slovakia (EU); e-mail: peter.stetka@euba.sk

² Bratislava University of Economics and Business, Faculty of Business Management, Dolnozemska cesta 1, 852 35 Bratislava, Slovakia (EU); e-mail: anna.hamranova@euba.sk

Abstract

This scientific study focuses on the analysis of artificial intelligence (AI) adoption for business process automation within the European Union and candidate countries, with particular emphasis on segmentation by enterprise size classes. The theoretical framework integrates the Technology-Organization-Environment (TOE) model, the Diffusion of Innovations theory, and the Resource-Based View (RBV), which together explain differences in firms' readiness and capacity to absorb technological innovations. The empirical section employs harmonized Eurostat microdata for the years 2024 and 2025, with the key indicator being the use of AI for predictive customer behavior analytics (indicator E_AI_PBAM). Using the non-parametric Kruskal–Wallis test, the study confirms that the level of AI implementation differs statistically significantly depending on firm size. The results reveal a systematic gradation: large enterprises dominate in terms of AI integration due to better access to resources and infrastructure, whereas micro and small enterprises face substantial knowledge and financial barriers despite exhibiting high year-on-year growth dynamics. The study identifies three stages in the adoption process—general availability, formal adoption, and practical day-to-day use by employees. The conclusions highlight the need for a differentiated EU digital policy that specifically addresses the barriers faced by smaller firms, and they underscore the strategic importance of developing dynamic capabilities for the long-term sustainability of AI solutions. This research contributes to the academic discourse by providing a statistically verified, pan-European quantification of the digital divide among enterprises.

1. Introduction

As the European Union accelerates its digital transformation agenda, artificial intelligence adoption for business process automation has emerged as a critical determinant of enterprise competitiveness across the single market. Across EU member states, governments and regulatory bodies have invested substantially in frameworks designed to stimulate AI deployment at the firm level, yet the empirical question of whether these investments translate into broadly distributed adoption gains or whether AI-driven automation remains concentrated among specific enterprise segments remains underexplored. Understanding the contours of this distribution is not merely an academic exercise; it carries direct consequences for the design of policies intended to close the digital divide, foster innovation, and sustain the productivity growth on which European economic resilience depends.

Despite growing policy interest in AI diffusion, systematic empirical evidence on how AI-driven process automation adoption varies across enterprise size classes within the EU remains scarce and methodologically underdeveloped. Existing studies tend either to rely on qualitative or single-country designs that preclude generalization or to aggregate firm-level data in ways that mask the within-size-class heterogeneity that is central to understanding adoption trajectories. In particular, the application of rigorous non-parametric statistical testing to EU-wide survey data — data that span dozens of member states and multiple enterprise categories — has not been systematically undertaken for the specific indicator of AI used for business process automation. This gap limits both scholarly understanding and the evidence base available to policymakers.

The remainder of this article is structured as follows: Section 2 establishes the theoretical background, introducing the Diffusion of Innovations Theory, the Technology–Organization–Environment framework, the Resource-Based View, the Dynamic Capabilities theory, institutional theories, and sociotechnical approaches as the primary conceptual lenses. Section 3 reviews the relevant empirical literature across three thematic streams. Section 4 describes the methodological approach, including the formulation of the hypothesis, the characteristics of the data source, the explanation of the research variables model, and the research sample. Section 5 presents the empirical results, including a descriptive analysis of the OBS_VALUE variable, the distributional characteristics of AI process automation adoption, and the statistical verification of the hypothesis. Section 6 discusses the findings in relation to theory and prior literature and draws policy and managerial implications. Section 7 concludes the article, summarizes the scientific contributions, and identifies directions for future research.

2. Theoretical Background

Artificial intelligence is currently regarded as one of the key general-purpose technologies that fundamentally influence the functioning of organizations, their processes, decision-making, and competitive positioning (Brynjolfsson & McAfee, 2014; Davenport & Ronanki, 2018). In business practice, AI is predominantly utilized in areas such as process automation, large-scale data processing, predictive analytics, and managerial decision support (Russell & Norvig, 2020).

Despite its considerable potential, the adoption of artificial intelligence is not uniform across the business population. Existing research highlights significant disparities in both the extent and manner of AI implementation between small and medium-sized enterprises (SMEs) and large organizations, driven by differences in resources, capabilities, organizational structures, and strategic orientation (Schwaeke et al., 2025; Aish & Noor, 2025). As such, the adoption of AI constitutes a complex process that extends beyond the technological dimension to include organizational, strategic, and environmental factors.

One of the principal theoretical approaches explaining the adoption of technological innovations is the Diffusion of Innovations theory, as developed by Rogers (2003). According to this framework, the rate and extent of innovation adoption are determined by attributes such as relative advantage, compatibility, complexity, trialability, and observability. In the context of artificial intelligence, this theory provides a basis for explaining differences in adoption behavior across firms of varying sizes. Large enterprises are more frequently classified as early adopters, as they exhibit a higher tolerance for risk, possess more extensive resources, and have greater capacity to experiment with emerging technologies (Rogers, 2003). In contrast, small and medium-sized enterprises tend to adopt AI more cautiously, with their decision-making being more strongly influenced by uncertainty regarding expected benefits and by the higher perceived complexity of the technology (Sánchez et al., 2025).

The most frequently applied framework in empirical research on the adoption of artificial intelligence in enterprises is the Technology–Organization–Environment (TOE) framework, originally developed by Tornatzky et al. (1990). This framework is based on the premise that decisions regarding technology adoption are shaped by three dimensions: technological, organizational, and environmental. The technological context encompasses the characteristics of AI solutions, such as their complexity, compatibility with existing systems, and perceived relative advantage. The organizational context reflects internal firm characteristics, particularly firm size, the availability of financial and human resources, top management support, and organizational culture. The environmental context accounts for competitive pressure, the regulatory environment, and the availability of a technological ecosystem (Tornatzky et al., 1990; Alka'awneh et al., 2025). The importance of firm size as an organizational factor is consistently confirmed by empirical studies, which point to higher organizational readiness and more advanced data infrastructure in large enterprises compared to SMEs (Badghish & Soomro, 2024). For this reason, the TOE framework represents an appropriate tool for systematically comparing AI adoption across different firm size categories.

A strategic perspective on the implementation of artificial intelligence is provided by the Resource-Based View (RBV), according to which a firm's competitive advantage derives from the possession

and effective utilization of valuable and difficult-to-imitate resources (Barney, 1991). In the context of AI, such strategically significant resources include high-quality datasets, expertise in data analytics, and an appropriate technological infrastructure (Dwivedi et al., 2021). Large enterprises typically have more favorable conditions for accumulating these resources, enabling them to develop proprietary AI solutions and integrate them into their long-term strategies. SMEs, by contrast, often rely on external solution providers, cloud services, or collaborative partnerships, which influences both the mode and scope of AI implementation (Aish & Noor, 2025). The RBV thus explains why identical technologies may generate heterogeneous performance outcomes depending on firm size and resource endowment.

The theory of dynamic capabilities builds upon the RBV and emphasizes a firm's ability to identify technological opportunities, integrate new technologies, and continuously reconfigure its resources and processes in response to a changing environment (Teece et al., 1997). The implementation of artificial intelligence is an ongoing process that requires continuous learning, algorithm refinement, and the adaptation of organizational routines. Large enterprises possess formalized processes and specialized teams; however, they often face organizational inertia that may slow down AI implementation. SMEs, in contrast, tend to be more flexible, yet their capacity to develop dynamic capabilities is constrained by limited capital and a shortage of specialized personnel (Schwaeke et al., 2025; Romeo & Lacko, 2026). The theory of dynamic capabilities therefore enables the analysis not only of AI adoption itself but also of its long-term sustainability.

Institutional theory highlights that organizations adopt AI also in response to normative, regulatory, and mimetic pressures from their environment (Romeo & Lacko, 2026). Large enterprises are typically subject to stronger expectations from regulatory authorities and the public, which motivates earlier AI adoption as well as the implementation of responsible AI principles (Akbarighatar, 2025). Sociotechnical approaches conceptualize AI as part of a broader system in which technology, human actors, and organizational structures interact. The implementation of AI reshapes job roles, competency requirements, and modes of collaboration, with these transformations manifesting differently in SMEs and large organizations (Dwivedi et al., 2021; Sánchez-Rodríguez et al., 2025).

These frameworks converge on a shared expectation: enterprise size, as a proxy for organizational resources, knowledge stocks, and environmental positioning, is associated with systematic variation in technology adoption rates. Based on the theoretical approaches discussed, the implementation of artificial intelligence in enterprises can be understood as a multidimensional phenomenon. Contemporary research therefore moves beyond the isolated application of individual theories and increasingly adopts an integrative perspective combining the TOE framework with the Diffusion of Innovations theory, the Resource-Based View, and the theory of dynamic capabilities (Alka'awneh et al., 2025; Sánchez-Rodríguez et al., 2025). Building on these theoretical foundations, the present study operationalizes firm size as the primary grouping variable in a non-parametric comparative analysis of AI-driven process automation adoption across the European Union, thereby empirically testing these theoretical propositions using official Eurostat survey data.

3. Literature Review

The systematic literature review is conducted in accordance with the PRISMA 2020 guidelines (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) (PRISMA, 2020). The objective is to identify, evaluate, and synthesize both empirical and conceptual insights into models of AI adoption in enterprises within the European Union, segmented by firm size. In line with the PRISMA 2020 methodology, it is necessary to formulate a primary research question based on the topic under investigation. This question can be stated as follows:

“Does the level of AI implementation in enterprises operating in Europe differ according to firm size?”

For the systematic analysis of scientific sources, the Web of Science citation database was utilized. To ensure a targeted selection of literature relevant to the research question, the PCC (Population–Concept–Context) framework was applied, along with predefined inclusion and exclusion criteria. The PCC framework was defined as follows:

- Population – enterprises operating within Europe
- Concept – adoption, implementation, use, or readiness for artificial intelligence technologies (including machine learning, natural language processing, computer vision, predictive analytics, etc.)
- Context – organizational, technological, economic, strategic, and regulatory contexts of business practice

The studies included in the analysis were selected based on the following criteria: focus on all firm size categories, AI adoption or use, publication period 2021–2025, document type limited to peer-reviewed articles, English language, and geographical focus restricted to European countries. Subsequently, exclusion criteria were applied, including studies addressing digital transformation without an explicit link to AI (e.g., focusing solely on IoT or ERP without an AI component), non-peer-reviewed sources (such as popular science articles, blogs, or media reports), unavailable full texts, and obvious duplicates. The literature selection process is illustrated in Figure 1.

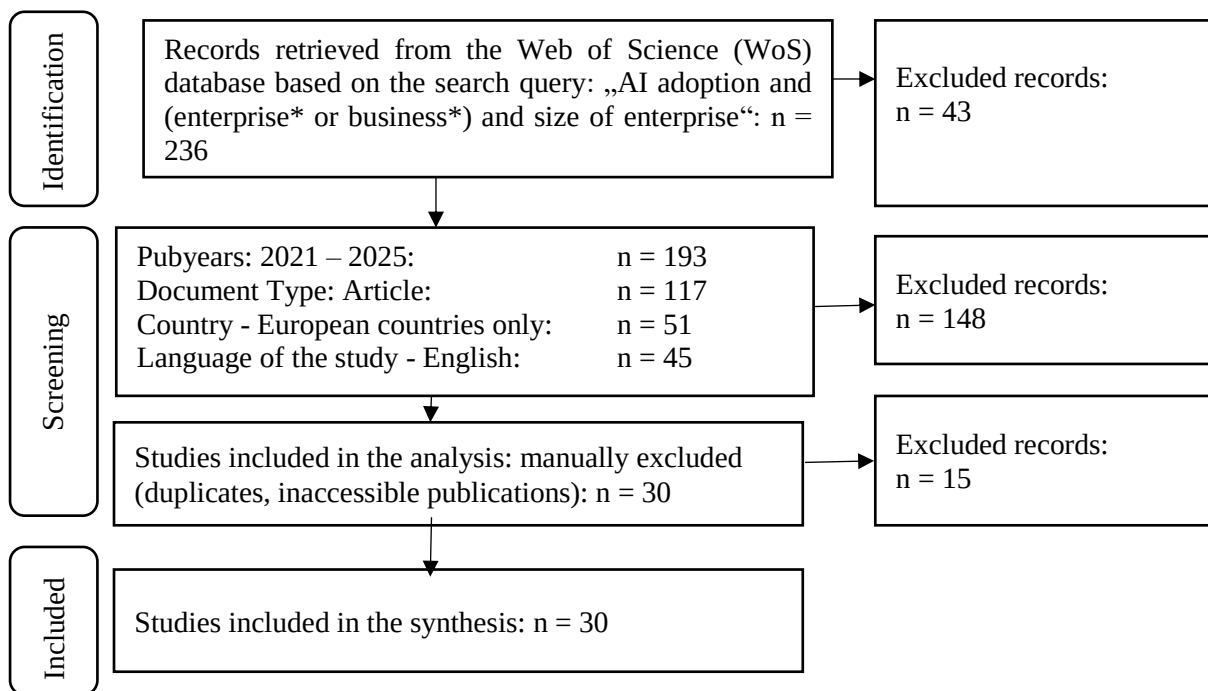


Figure 1. PRISMA flow diagram.

3.1 AI Adoption Determinants in Organizations

The adoption of artificial intelligence (AI) in enterprises is a complex process influenced by a range of factors, most commonly examined through the Technology–Organization–Environment (TOE) framework (Apostoaie et al., 2025; Sánchez et al., 2025). This model is further complemented by additional psychological and strategic perspectives that shape managerial willingness to invest in emerging technologies. These include:

Technological determinants

These focus on the technical readiness of firms and the characteristics of the innovation itself:

- **Technological readiness and infrastructure** – firms require not only digital maturity but also access to high-performance hardware and cloud infrastructure (Añón Higón & Torrent-Sellens, 2025).
- **Data (quality, volume, and accessibility)** – the availability, scale, and quality of data are key enablers of AI adoption, while effective data management is essential for system scalability (Oldemeyer et al., 2025).

- **Relative advantage and compatibility** – the perceived benefits of AI compared to legacy systems, as well as its alignment with existing business processes, significantly increase the likelihood of adoption (Añón Higón & Torrent-Sellens, 2025; Apostoaie et al., 2025).
- **Perceived complexity** – higher implementation difficulty and algorithmic complexity act as barriers, particularly for firms with lower levels of digital maturity (Apostoaie et al., 2025).

Organizational determinants

These refer to internal firm characteristics, resources, and culture that are essential for successful AI integration:

- **Top management support** – leadership attitudes and willingness to allocate resources and define a clear AI strategy are considered among the strongest predictors of successful adoption (Apostoaie et al., 2025).
- **Skills and human capital** – the lack of employees with relevant technical and digital skills is identified as a critical barrier, making continuous learning and upskilling essential (Añón Higón & Torrent-Sellens, 2025; Huseyn et al., 2024).
- **Financial resources** – high initial costs of acquiring, operating, and maintaining AI systems represent a major constraint, particularly for small and medium-sized enterprises (SMEs) (Oldemeyer et al., 2025).
- **Organizational culture and innovation climate** – a culture that encourages experimentation and transformation facilitates employee acceptance of technological change (Oldemeyer et al., 2025).
- **Firm size and age** – larger and more established firms generally have greater resource capacity for adoption, although dynamic startups often demonstrate higher agility in implementing innovations (Añón Higón & Torrent-Sellens, 2025; Arroyabe et al., 2024).

Environmental (external) determinants

These include external pressures from the firm's environment that drive innovation:

- **Competitive and customer pressure** – the need to maintain market position and respond to customer demands for personalization creates strong push-and-pull effects (Apostoaie et al., 2025).
- **Regulatory framework and ethical standards** – legislation (e.g., the EU AI Act) and compliance with ethical data use standards define the boundaries and safety conditions for AI deployment (Štrukelj & Dankova, 2025).
- **Ecosystem and vendor support** – access to external consultancy, vendor support, and collaboration with universities significantly facilitates organizational learning and adoption processes (Añón Higón & Torrent-Sellens, 2025; Apostoaie et al., 2025).

Strategic, psychological, and ethical factors

These extend beyond the TOE framework and shape managerial perceptions of technology:

- **Perceived value and agility** – managers base adoption decisions on expected performance improvements and the extent to which AI enhances organizational agility (Kukanja & Planic, 2025; Maldonado-Canca et al., 2026).
- **Anthropomorphism** – attributing human-like characteristics to AI systems (e.g., generative models) increases perceived ease of use and user enjoyment (Gupta, 2025).
- **Perceived risks and trust** – concerns regarding cybersecurity, privacy protection, and fears of job displacement act as barriers to AI adoption (Bağ et al., 2024; Maldonado-Canca et al., 2026; Štrukelj & Dankova, 2025).

Overall, research indicates that AI adoption is not determined by a single factor, but rather by a combination of technological readiness, organizational capacity, and external environmental pressures (Bağ et al., 2024; Sánchez et al., 2025).

3.2 AI Applications Across Business Sectors and Functions

Applications of artificial intelligence (AI) in the literature cover a broad range of industries and business functions, transforming traditional operational models from the automation of routine tasks to the augmentation of human capabilities in complex decision-making processes (Ayinaddis, 2025). The extensive application of AI in industry and manufacturing is addressed by Bunte et al. (2021), who state that AI enables anomaly detection, leading to significant resource optimization. Oldemeyer et al. (2025) further add that AI is used for improved production control, quality assurance, and machine failure prediction. Dalle-Pezze et al. (2015) emphasize the use of classification methods for predictive maintenance, enabling dynamic scheduling of service intervals. Dos Santos et al. (2021) describe the application of digital twins in supporting operational planning in manufacturing. Farahnakian et al. (2021) demonstrate the use of deep learning for automated defect detection in warehouse environments.

In marketing and sales, Chatterjee et al. (2023) report that AI systems within Customer Relationship Management (CRM) analyze purchasing preferences and customer interactions to provide personalized offers and product recommendations. Islam et al. (2024) and Mariani et al. (2022) highlight the strategic value of predictive analytics in anticipating market changes and optimizing commercial strategies, while Mishra and Pani (2021) describe the application of AI in segmenting customers based on lifestyle and preferences.

In customer service, Paschen et al. (2019) and Benbya et al. (2020) show that chatbots and virtual assistants are widely used, enabling efficient customer support at any time and from any location. Gabelaia et al. (2024) confirm that these tools increase customer satisfaction. Brill et al. (2022) examine customer satisfaction with voice assistants such as Alexa and Siri.

In financial services and insurance, fraud detection and risk assessment are key applications. Floridi et al. (2018) and Hendieh et al. (2023) identify AI as a crucial tool for fraud detection and risk modelling, thereby enhancing financial security. Aly et al. (2021) propose decision tree-based models for predicting bankruptcy in small and medium-sized enterprises. Bian et al. (2019) report AI applications in algorithmic trading and investment portfolio management.

In human resource management (HR), AI is applied to recruitment and talent selection. Khatri et al. (2019) and Van den Broek et al. (2021) focus on the integration of AI into hiring decision-making processes. Vedapradha et al. (2024) specifically address talent acquisition in higher education institutions. Wamba-Taguimdje et al. (2020) highlight the use of robotic process automation for automated email processing.

AI also has wide applications in other sectors. In healthcare, Jarrahi (2018) describes the use of computer vision for MRI image analysis, where AI assists physicians in identifying even minor pathologies such as hemorrhages. Makarius et al. (2020) highlight the use of surgical robots assisting physicians in complex operations. In agriculture, Bughin et al. (2018) report that AI-based monitoring systems analyze soil health and crop conditions in real time. In logistics, transport, and energy, Benbya et al. (2020) identify leading applications such as autonomous vehicles and drone-based delivery systems. Yu et al. (2019) describe the use of AI for optimizing transport routes and logistics flows. Sánchez et al. (2025) and Niet et al. (2023) note that AI improves demand forecasting in the energy sector and reduces operational costs in infrastructure management, such as data center cooling.

Finally, in business administration, Mihai et al. (2023) state that AI optimizes workflows and reduces costs. Gupta (2025) emphasizes that tools such as ChatGPT can support entrepreneurs in business model innovation, international market research, and code generation and debugging. Marrella (2019) highlights the use of AI for document management automation and meeting scheduling.

3.3 Digital Transformation and SME Challenges

The digital transformation of small and medium-sized enterprises (SMEs) is associated with a complex set of challenges, primarily stemming from their structural constraints and limited resource endowments compared to large corporations. Among the most significant limitations faced by SMEs are financial and economic barriers. Bąk et al. (2024) as well as Bunte et al. (2021) report that a lack of capital represents one of the most critical obstacles preventing SMEs from investing in artificial intelligence (AI) technologies. Dvořáková et al. (2021) and Oldemeyer et al. (2025) further note that SMEs face high initial costs related to hardware and software acquisition, while also struggling to accurately estimate return on investment (ROI). Sánchez et al. (2025) add that SMEs have more limited access to external credit and capital resources for innovation projects compared to large corporations.

Another key challenge is the knowledge barrier and shortage of talent. The lack of in-house experts and insufficient digital skills constitute major obstacles to AI implementation in smaller firms (Huseyn et al., 2024; Oldemeyer et al., 2025). SMEs are often unable to compete financially with large enterprises in recruiting specialists such as data scientists (Oldemeyer et al., 2025). A pronounced gap in upskilling is also evident, with AI-related training reaching significantly fewer operational employees compared to managerial staff. Many SME managers lack a clear understanding of the practical applications of AI, which contributes to hesitation in its adoption (Bhalerao et al., 2022; Oldemeyer et al., 2025).

Further studies identify low technological and infrastructural readiness, including outdated technical infrastructure (Añón Higón & Torrent-Sellens, 2025; Arroyabe et al., 2024) and poor data quality (Oldemeyer et al., 2025). Organizational and cultural factors also play a significant role, such as resistance to change (Oldemeyer et al., 2025) and weak top management support (Kukanja & Planic, 2025; Oldemeyer et al., 2025). These challenges are further compounded by issues related to regulation, ethics, and security (Stojanovska-Stefanova et al., 2025; Štrukelj & Dankova, 2025; Arroyabe et al., 2024; Oldemeyer et al., 2025).

Despite this body of evidence, no study has applied rigorous non-parametric statistical testing to cross-country Eurostat microdata to quantify and rank the magnitude of size-class disparities in AI-specific process automation adoption across the full EU enterprise population. While the literature provides a rich contextual understanding of why size-class gradients in AI adoption exist, it does not offer the statistically validated, population-representative quantification required for evidence-based EU digital policy. The present study directly addresses this gap.

4. Methodology

The empirical analysis draws on the Eurostat Community Survey on ICT Usage and E-Commerce in Enterprises (Eurostat, 2026), a harmonised annual survey conducted across all EU Member States that provides nationally representative data on enterprise technology adoption. The specific indicator analysed is E_AI_PBA, which measures the percentage of enterprises reporting the use of artificial intelligence technologies for business process automation. The methodology consists of the formulation of research hypotheses, the description and preprocessing of the data source, the specification of the research variables model, and the construction of the analytical sample.

4.1 Formulation of the Research Hypothesis

The research hypothesis builds on the research question and is formulated in both null and alternative form as follows:

H0: The level of AI implementation in enterprises operating in Europe does not differ according to firm size.

H1: The level of AI implementation in enterprises operating in Europe differs statistically significantly according to firm size.

4.2 Data Source and Data Preparation

The data used in this study originate from the Eurostat database, specifically from the dataset ISOC_EB_AI – Use of artificial intelligence by enterprises, which is part of the Information Society statistics. The ISOC_EB_AI dataset provides harmonised data on the use of artificial intelligence technologies by enterprises in European Union countries and selected additional states (Eurostat, 2026). The primary data source is the regular statistical survey on ICT usage in enterprises, conducted by national statistical offices of EU Member States in accordance with Eurostat methodological guidelines. The survey is mandatory for all Member States and is carried out on an annual basis. The target population consists of enterprises with at least 10 employees, although Eurostat does not explicitly include all such firms uniformly. An exception applies to micro-enterprises, which are included only in countries where the national statistical office incorporates them into the survey (Eurostat, 2025).

The sampling design is based on stratified sampling according to firm size, economic activity (NACE Rev. 2 classification), and country. The collected data are subsequently weighted to produce estimates representative of the full population of enterprises in each country. Data collection is conducted using a standardized questionnaire, ensuring cross-country comparability. The survey is primarily administered electronically (online questionnaires and electronic reporting), and in some cases supplemented by administrative data available to national statistical authorities.

The use of artificial intelligence in the survey is defined as the deployment of selected technologies, including machine learning, natural language processing, image and speech recognition, automated decision-making systems, or big data analytics. Individual indicators in the dataset (denoted by codes such as E_AI_...) capture either the use of specific AI technologies or their aggregated occurrence. For example, E_AI_TANY represents enterprises using at least one AI technology, E_AI_BLE refers to machine learning, E_AI_BIAS indicates AI bias detection, and E_AI_EC refers to AI used in e-commerce. The reported values are most commonly expressed as the percentage of enterprises that meet a given AI indicator (e.g., using at least one AI technology) relative to the total number of enterprises within a specific size class, industry, and country. The data are aggregated and anonymized in compliance with statistical confidentiality rules. They reflect the presence of AI usage rather than its intensity, economic impact, or technological sophistication. At the same time, some time series may be influenced by methodological changes, revisions in the definition of artificial intelligence, or cross-country differences in survey responses.

4.3 Descriptive Profiling

The research variable model was derived from the source dataset provided by Eurostat (Eurostat, 2026), with the first part of the source file illustrated in Figure 2. The list of variables and their corresponding definitions is presented in Table 1.

DATAFLOW	LAST UPDATE	freq	size_emp	nace_r2	indic_is	unit	geo	TIME_PE	RIOD	OBS	VALUE
ESTAT:ISOC_EB_AI(1.0)	2/27/2026 11:00 A	A	0-9	C10-S951_X_K_E_AIX_CC1SIX_DA	PC_ENT	ES		2023		5.74	
ESTAT:ISOC_EB_AI(1.0)	2/27/2026 11:00 A	A	0-9	C10-S951_X_K_E_AIX_CC1SIX_DA	PC_ENT	ES		2024		5.66	
ESTAT:ISOC_EB_AI(1.0)	2/27/2026 11:00 A	A	0-9	C10-S951_X_K_E_AIX_CC1SIX_DA	PC_ENT	ES		2025		5.49	
ESTAT:ISOC_EB_AI(1.0)	2/27/2026 11:00 A	A	0-9	C10-S951_X_K_E_AIX_CC1SIX_DA	PC_ENT	PT		2023		13.36	

Figure 2. Excerpt from the source dataset

Table 1. Definition of research variables

Variable	Meaning	Values (examples of possible values)
DATAFLOW	Dataset identifier in the Eurostat database, used for the technical identification of the data flow	ESTAT:ISOC_EB_AI(1.0)
LAST UPDATE	Date and time of the last data update in the Eurostat database	MM/DD/YYYY HH:MM:SS
Freq	Data periodicity	A = annual (yearly data)
Size_emp		micro enterprises: fewer than 10 employees

	Enterprise size class based on the number of employees, defined according to Eurostat methodology; overlapping employee count categories are excluded from the evaluation	small enterprises: 10–49 employees medium-sized enterprises: 50–249 employees large enterprises: 250 or more employees
Nace_r2	Economic classification of industries according to NACE Rev. 2, used for sectoral comparisons	C10–S951_X_K – aggregation of multiple sections (manufacturing and services, excluding selected sectors)
Indic_is	Key analytical column indicating the type of artificial intelligence indicator (exact Eurostat nomenclature)	E_AI_PBAM – share of enterprises using artificial intelligence for predictive analytics, specifically for predicting user or customer behaviour (predictive analytics / behaviour analysis)
		E_AI_BIAS – detection of AI bias
		E_AI_EC – artificial intelligence used in e-commerce
Unit	Unit of measurement; values are expressed as percentage shares	PC_ENT – percentage of enterprises meeting a specific AI indicator (general availability of AI)
		PC_ENT_AI_TANY – percentage of enterprises using at least one AI technology (AI adoption)
		PC_ENT_IUSE – percentage of enterprises using AI in the execution of work tasks (daily use of AI)
Geo	Geographical area (ISO country codes); aggregated values (e.g. EU_27) are excluded from the analysis	SK, PT, ES, DE, SE...
TIME_PERIOD	Reference year of data collection	2024, 2025
OBS_VALUE	Observed value of the indicator, expressing the percentage of enterprises that meet the condition defined by the indicator	4.52 = 4.52% of enterprises

The primary analysed variable was OBS_VALUE, which represents the percentage share of enterprises meeting a given indicator. Another important variable is the unit variable, which can take three different values: PC_ENT, PC_ENT_AI_TANY, and PC_ENT_IUSE. These categories capture different stages of the AI implementation process—from general availability, through formal adoption, to daily use by employees. The variable PC_ENT (percentage of enterprises) expresses the proportion of enterprises within a given size class that satisfy a specific artificial intelligence indicator, relative to the total number of enterprises in that category. The base for calculating PC_ENT, PC_ENT_AI_TANY, and PC_ENT_IUSE (denominator) is the total number of enterprises within a given size class, country, and year. The numerator consists of enterprises that reported using the respective technology (i.e., the specific AI indicator). Formally, the calculation of PC_ENT can be expressed as follows:

$$PC_ENT = \frac{\text{number of enterprises meeting a specific AI indicator}}{\text{total number of enterprises in the given size class}} * 100$$

The variable PC_ENT_AI_TANY represents the percentage of enterprises that use at least one of the defined artificial intelligence technologies, regardless of the extent or intensity of their use. Within the survey, artificial intelligence technologies include in particular: text analysis (text mining), speech recognition, natural language generation, image recognition, machine learning, AI-based process automation, as well as autonomous systems and robots. The denominator is again the total number of enterprises within a given size class. This indicator therefore reflects the general level of AI adoption across enterprises.

$$PC_ENT_AI_TANY = \frac{\text{number of enterprises using at least one AI technology}}{\text{total number of enterprises in the given size class}} * 100$$

The variable PC_ENT_IUSE represents the percentage of enterprises in which employees actively use artificial intelligence technologies in the performance of their work. This indicator has a stricter meaning than PC_ENT or PC_ENT_AI_TANY, as it reflects the practical and daily use of AI rather than its mere availability or experimental testing. From a methodological perspective, an enterprise is included in this category only if artificial intelligence is actively used by its employees within operational business processes.

$$PC_ENT_IUSE = \frac{\text{number of enterprises using artificial intelligence technologies in the execution of work tasks}}{\text{total number of enterprises in the given size class}} * 100$$

The data were processed using quantitative methods of descriptive statistics. Values of the OBS_VALUE variable were transformed into numerical format; non-standard categories indicated by symbols (e.g., “u”, “C”) were treated as missing values and were excluded from the calculations.

The full research sample consisted of 72,312 enterprises covering the years 2021, 2023, 2024, and 2025, during which all Eurostat indicators in the E_AI_* group (n = 53) were examined. In this article, the analysis focuses on a single indicator, namely E_AI_PBAM, which stands for:

E – Enterprises, AI – Artificial Intelligence, P – Predictive, BA – Behaviour Analysis, M – Methods/Models.

This indicator measures the proportion of enterprises using artificial intelligence for predictive analytics, specifically for predicting user or customer behaviour. An additional restriction concerned the time horizon, as only the most recent two years were analysed (2024 and 2025). This reduced the initial research dataset to 1,061 records. After excluding aggregated values (e.g., EU27) and overlapping observations, the resulting analytical sample consisted of 629 enterprises, of which 315 were from 2024 and 314 from 2025. Furthermore, records with missing OBS_VALUE data were excluded. In 2024, 21 records were removed, leaving 294 observations for analysis, while in 2025, 9 records were excluded, resulting in 305 valid observations. The percentage distribution of the final analytical samples is presented in Figure 3 and Figure 4.

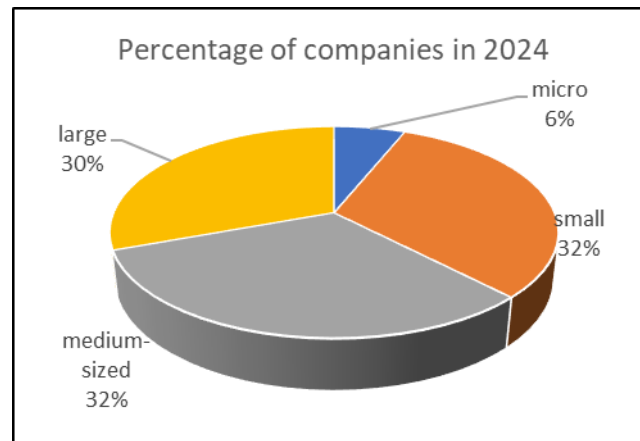


Figure 3. Research sample for the year 2024.

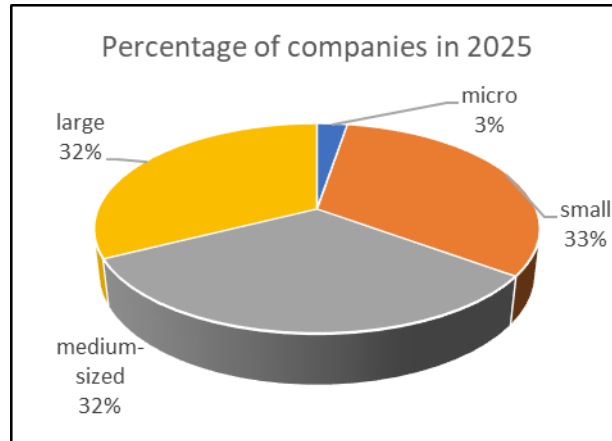


Figure 4. Research sample for the year 2025.

5. Results

The Results section includes: descriptive analysis of the OBS_VALUE variable, distributional characteristics of AI process automation adoption, and statistical testing of the hypothesis.

5.1 Descriptive analysis of the OBS_VALUE variable

The descriptive analysis of the OBS_VALUE variable was conducted separately for data collected in 2024 and 2025. In 2024, 294 valid observations were analysed, while in 2025 the sample included 305 observations. In both cases, the sample sizes are sufficient for statistical evaluation. The results of the descriptive analysis for each year are presented in Table 2.

Table 2. Results of the descriptive analysis of the OBS_VALUE variable

	OBS_VALUE 2024	OBS_VALUE 2025
N	294	305
Mean	15.4688	19.6674
Std. error mean	0.7988	0.8364
95% CI mean lower bound	13.8968	18.0215
95% CI mean upper bound	17.0409	21.3133
Median	10.11	16.71
Mode	2.56	26.84
Standard deviation	13.6957	14.6073
Variance	187.5732	213.372
IQR	20.7	25.18
Range	53.99	59.96
Minimum	0.06	1.3
Maximum	54.05	61.26
Skewness	0.8452	0.5396
Std. error skewness	0.1421	0.1396
Kurtosis	-0.3412	-0.8063
Std. error kurtosis	0.2833	0.2783
25th percentile	3.65	6.46
50th percentile	10.11	16.71
75th percentile	24.35	31.64

In 2024, the mean value of the OBS_VALUE variable reached 15.47, while the median was considerably lower (10.11). This difference indicates an asymmetric distribution of values,

characterised by a higher frequency of lower values and a smaller number of high values that increase the arithmetic mean. In 2025, the mean value increased to 19.67, while the median reached 16.71. Compared to 2024, the difference between the mean and median is less pronounced, suggesting a more balanced distribution of data. Overall, this indicates an increase in typical OBS_VALUE levels in 2025.

Data variability was relatively high in both years. In 2024, the standard deviation increased to $SD = 13.70$, and the overall range of values was 53.99 (from 0.06 to 54.05). The interquartile range amounted to 20.70, indicating substantial dispersion within the central 50% of the data. In 2025, variability increased slightly further ($SD = 14.61$), while the range expanded to 59.96 (from 1.30 to 61.26). The interquartile range reached 25.18, indicating greater dispersion of values compared to the previous year.

The skewness analysis shows that the distribution of OBS_VALUE is right-skewed in both years. In 2024, skewness was higher (0.85), indicating a stronger concentration of lower values and a longer right tail of the distribution. In 2025, skewness decreased to 0.54, suggesting a weaker asymmetry and a closer approximation to a symmetric distribution. In both years, kurtosis was negative (2024: -0.34 ; 2025: -0.81), indicating a platykurtic distribution, i.e., a flatter distribution shape compared to the normal distribution, with a lower occurrence of extreme values.

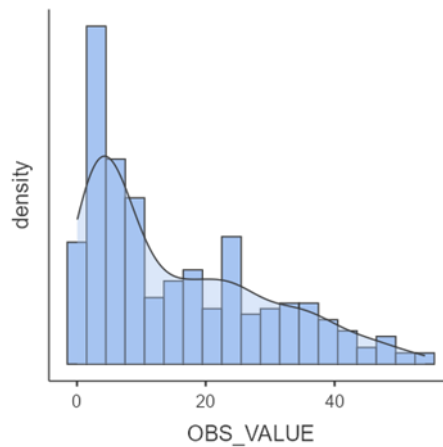


Figure 5. Histogram for 2024.

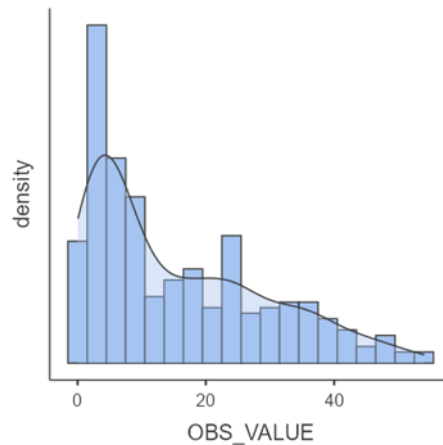


Figure 6. Histogram for 2025.

The histogram for 2024 visually confirms a significant concentration of values in the lower intervals of the scale and a gradual right-sided tail towards higher values. The distribution appears uneven, with a dominant occurrence of values below the median. The histogram for 2025 shows a shift of the distribution towards higher values and a more even distribution of frequencies. The right-sided

asymmetry is still present, but less pronounced, which corresponds to a reduced value of the skewness coefficient and a higher median.

Based on the descriptive statistics and graphical display, it can be stated that between 2024 and 2025 there was a shift of the distribution of the OBS_VALUE variable towards higher values, accompanied by slightly higher variability and a more even distribution of the data. Nevertheless, the distributions in both years remain deviated from the normal distribution, which will be taken into account when choosing appropriate inferential statistical methods.

5.2 Distributional Characteristics of AI Process Automation Adoption

The analysis of the OBS_VALUE variable was conducted with respect to differentiation by the UNIT variable, which represents three distinct indicators: PC_ENT, PC_ENT_AI_TANY, and PC_ENT_IUSE. The data are further disaggregated by enterprise size category (micro, small, medium, and large enterprises). Table 4 presents the mean values of the OBS_VALUE variable according to UNIT and firm size, as well as the year-on-year percentage change and the absolute year-on-year change.

Table 3. Evaluation of the OBS_VALUE variable by firm size and UNIT variable

Variable UNIT	Enterprise size	Average OBS_VALUE 2024	Average OBS_VALUE 2025	Year-on-year change (%)	Absolute year-on-year change
PC_ENT - Percentage of enterprises meeting a specific AI indicator (general availability of AI)	micro	1.49	3.73	150.34	2.24
	small	3.24	5.00	54.32	1.76
	medium-sized	6.26	10.12	61.66	3.86
	large	15.15	21.51	41.98	6.36
PC_ENT_AI_TANY - Percentage of enterprises using at least one AI technology (AI adoption)	micro	18.45	22.71	23.09	4.26
	small	28.08	30.00	6.84	1.92
	medium-sized	30.82	35.05	13.72	4.23
	large	36.38	41.27	13.44	4.89
PC_ENT_IUSE - Percentage of enterprises using AI in daily work processes (everyday use of AI)	micro	1.59	3.91	145.91	2.32
	small	3.28	5.06	54.27	1.78
	medium-sized	6.29	10.15	61.37	3.86
	large	15.18	21.54	41.90	6.36

Table 3 provides a comprehensive overview of the development of the average values of the OBS_VALUE variable in 2024 and 2025, disaggregated by unit (PC_ENT, PC_ENT_AI_TANY, PC_ENT_IUSE) and firm size (micro, small, medium-sized, and large enterprises). The results clearly indicate a substantial increase in the observed indicator across all categories, although the intensity of this growth varies depending on both the UNIT variable and firm size.

In the case of the PC_ENT variable, a pronounced year-on-year increase is observed across all firm size categories, particularly among micro enterprises, where the value rises from 1.49 in 2024 to 3.73 in 2025. This corresponds to the highest relative change (+150.34%), although the absolute change remains relatively modest (+2.24). This finding suggests that even small absolute increases can translate into substantial percentage growth when starting from a low baseline. For small and medium-sized enterprises, the percentage growth is more moderate (+54.32% and +61.66%, respectively), while the absolute change gradually increases (+1.76 to +3.86). Large enterprises exhibit the highest absolute increase (+6.36), but the lowest relative growth (+41.98%), indicating a more stable and less dynamic development pattern among larger entities.

For the PC_ENT_AI_TANY unit, OBS_VALUE levels are substantially higher in both years compared to other units, confirming a broader diffusion of at least occasional AI usage. However, the year-on-year growth is relatively moderate compared to PC_ENT and PC_ENT_IUSE. The highest relative increase is again observed among micro enterprises (+23.09%, absolute +4.26), while small enterprises show only marginal growth (+6.84%, +1.92). Medium-sized and large enterprises exhibit similar dynamics (approximately +13–14%), with absolute increases of around +4 to +5 percentage points. These results suggest that broader AI usage is already largely established in these groups, and further growth is gradual rather than exponential.

The PC_ENT_IUSE unit follows a similar pattern to PC_ENT, although with slightly higher percentage increases. Micro enterprises again dominate, with a year-on-year change of +145.91% (absolute +2.32). This sharp increase indicates a rapid intensification of AI usage in the least digitally mature firms. For small and medium-sized enterprises, percentage changes range between +54% and +61%, while large enterprises show the highest absolute increase (+6.36) but the lowest relative growth (+41.90%). This pattern confirms that growth in large enterprises is driven more by expansion of existing capabilities than by fundamental changes in adoption behaviour. The results for the individual stages of AI adoption in enterprises are illustrated in Figures 7, 8, and 9.

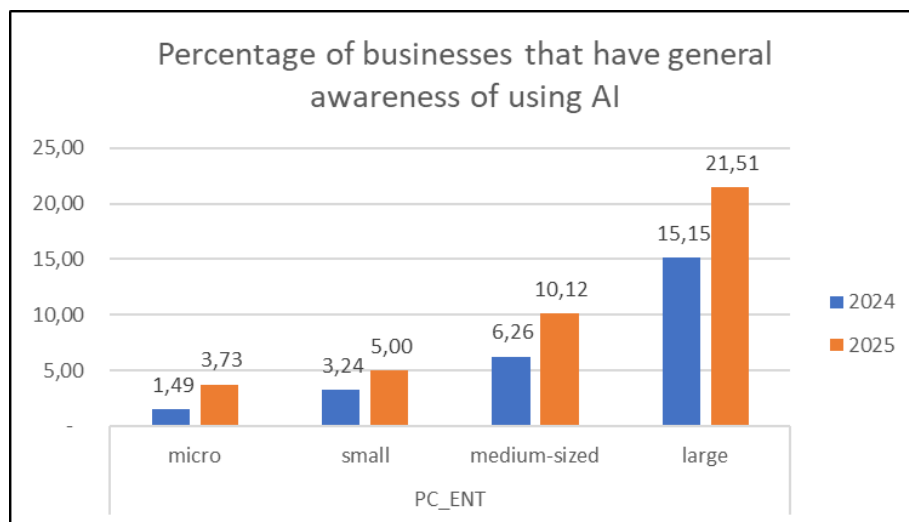


Figure 7. Businesses with general awareness of the use of AI

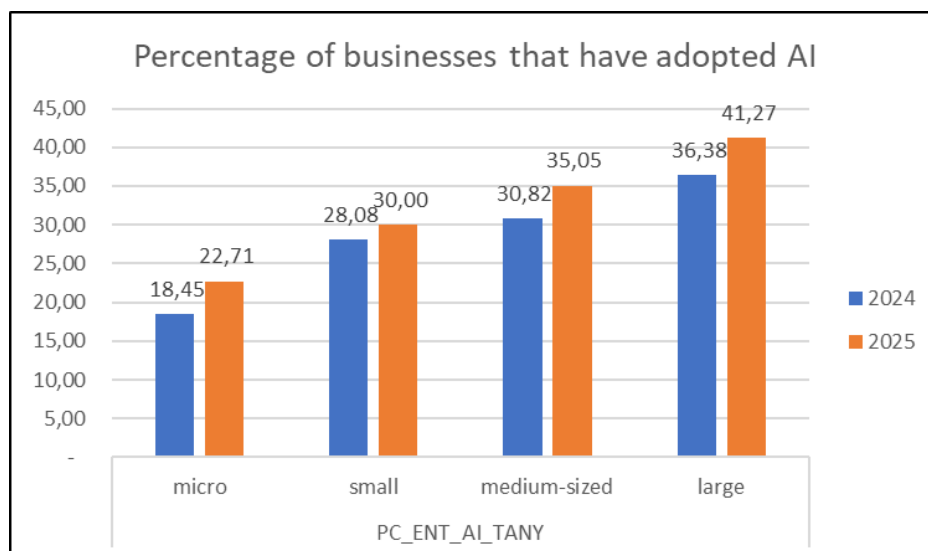


Figure 8. Businesses that have adopted AI

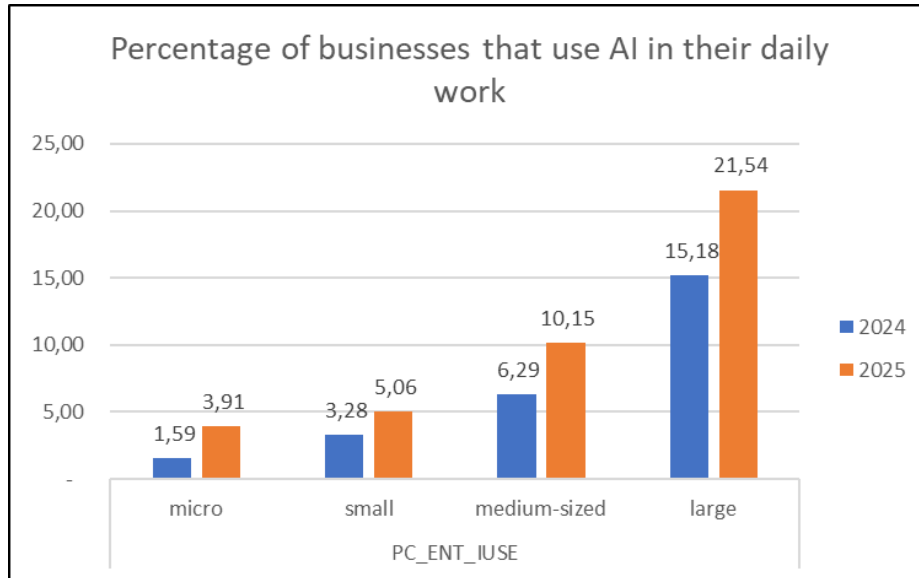


Figure 9. Businesses with daily use of AI

The higher values of the PC_ENT_AI_TANY indicator compared to PC_ENT and PC_ENT_IUSE are explained by differences in the methodological definitions of the respective indicators. PC_ENT_AI_TANY captures the broadest form of artificial intelligence adoption, as it measures the proportion of enterprises using at least one AI technology, regardless of the scope, frequency, or level of integration into business processes.

In contrast, the PC_ENT and PC_ENT_IUSE indicators apply stricter criteria. PC_ENT focuses on enterprises in which AI is systematically available or formally implemented, while PC_ENT_IUSE captures regular or even daily use of AI in the execution of work tasks. These indicators therefore represent narrower subsets of enterprises that are in more advanced stages of AI adoption.

The higher values of PC_ENT_AI_TANY across all firm size categories reflect the fact that experimental, occasional, or individual use of AI tools (e.g., external cloud-based applications) is significantly more widespread than their systematic or fully integrated use at the enterprise level. Consequently, the indicators do not represent alternative measures of the same phenomenon, but rather a hierarchy of AI adoption stages, ranging from basic exposure to technology to its routine integration into business processes.

Overall, it can be concluded that the percentage year-on-year change is highest among micro enterprises, largely due to the low baseline values observed in 2024. In contrast, absolute changes increase with firm size, reaching their maximum among large enterprises. The PC_ENT_AI_TANY indicator shows a more stable and less dynamic growth pattern, suggesting a certain degree of market saturation, whereas the PC_ENT and PC_ENT_IUSE indicators reflect a continuing adoption phase, particularly among smaller enterprises.

Previous results indicate that the level of AI implementation, adoption, and usage differs statistically significantly according to firm size. This statement was statistically verified using an appropriate statistical test in the Jamovi program, separately for the 2024 data and separately for the 2025 data.

Testing of the 2024 dataset: first, the normality of the research sample was tested using the Shapiro–Wilk test, which recorded values ($W = 0.8841$, $p < 0.0001$), meaning that the OBS_VALUE variable is not normally distributed and the assumption of normality is violated. For this reason, a non-parametric Kruskal–Wallis test was used, where the independent variable was firm size and the dependent variable was OBS_VALUE.

Result of the test: the Kruskal–Wallis test was applied to verify differences in the observed variable OBS_VALUE between four independent groups (defined by firm size). The results indicate a significant group effect, $\chi^2(3) = 55.31$, $p < 0.0001$, which indicates that the distributions (or medians) of the compared groups differ statistically significantly. The effect size $\varepsilon^2 = 0.1888$ indicates a

substantial magnitude of the effect, with approximately 19% of the variability in the observed variable attributable to differences between groups.

Similar results were obtained for the 2025 dataset. The Shapiro–Wilk test reached values $W = 0.9387$, $p < 0.0001$, indicating a violation of normality. The results of the subsequent Kruskal–Wallis test, as in the previous case, indicate a significant group effect, $\chi^2(3) = 63.91$, $p < 0.0001$, which indicates that the distributions (or medians) of the compared groups differ statistically significantly. The effect size $\epsilon^2 = 0.2102$ indicates a substantial magnitude of the effect, with approximately 21% of the variability in the observed variable attributable to differences between groups.

From the results of both tests, it follows that we can reject the null hypothesis and accept the alternative hypothesis H1: The level of AI implementation in enterprises operating in Europe differs statistically significantly according to firm size.

5.3 Disaggregated Group-Level Statistics

Disaggregated group-level statistics reveal a nuanced size-class ranking that warrants careful interpretation. Ranked in descending order of mean adoption rate across the five mutually exclusive groups, the ordering is as follows: "From 0 to 1 person employed" (22.48%), "250 persons employed or more" (14.29%), "From 2 to 9 persons employed" (10.16%), "From 50 to 249 persons employed" (10.16%), and "From 10 to 49 persons employed" (9.39%). Because there are only five groups, the top-three and bottom-three rank positions structurally overlap: "From 2 to 9 persons employed," which ranks third-highest, simultaneously ranks third-lowest (i.e., occupies the middle position). Rather than presenting separate top and bottom lists that produce this misleading appearance of contradiction, the full ordered ranking is reported here to provide an unambiguous account of the size-class gradient.

The appearance of the "From 0 to 1 person employed" category at the top of this descriptive ranking requires substantial qualification and must be interpreted alongside the inferential results. This group's mean of 22.48% numerically exceeds the large-enterprise mean of 14.29%, yet no statistically significant pairwise difference between these groups was detected in Dunn post-hoc testing. This apparent discrepancy — a higher descriptive mean for micro-enterprises without inferential confirmation of superiority — is explained by the conjunction of two factors. First, the group contains only $N = 3$ observations, yielding a 95% confidence interval that spans more than 85 percentage points and crosses zero, rendering the group mean an unreliable summary statistic. With $N = 3$, the standard error is so large that no pairwise comparison involving this group can reach statistical significance regardless of the observed mean difference. Second, the elevated mean most likely reflects a small number of EU member states — potentially those with high concentrations of tech-oriented sole traders or particular survey sampling characteristics — where a subset of micro-enterprises report AI automation use, thereby pulling the group average upward substantially. The descriptive rank of this group thus reflects extreme between-country heterogeneity rather than genuinely widespread micro-enterprise AI adoption. Findings for this group should be treated as inconclusive rather than substantively informative, and the "From 0 to 1 person employed" category should not be identified as a high-adoption segment on the basis of the current data. Cross-national variation in the micro-enterprise segment is thus a central analytical challenge that future research, particularly research with richer country-level micro-enterprise data, should address directly.

In contrast, the "250 persons employed or more" group's position as the second-ranked group by mean adoption rate is reinforced by the inferential analysis: this group generates the only statistically significant pairwise differences in the entire comparison set, and its $N = 102$ observations provide a substantially more reliable basis for inference. The inferential and descriptive rankings thus converge on large enterprises as the dominant adopter class in a meaningful and statistically defensible sense. Table 4 presents the full group-level descriptive statistics for the five mutually exclusive size classes, and Table 5 provides corresponding descriptive information for the three aggregate categories.

Table 4. Group Statistics — Enterprises using AI technologies f

Group	N	Mean (%)	Median (%)	SD	CI95_low	CI95_high
From 0 to 1 person employed	3	22.48	0.78	37.89	-20.4	65.36
250 persons employed or more	102	14.29	9.4	12.62	11.84	16.74
From 0 to 9 persons employed	6	10.23	1.57	15.68	-2.32	22.78
From 2 to 9 persons employed	8	10.16	1.71	16.75	-1.44	21.77
From 50 to 249 persons employed	102	10.16	4.23	11.93	7.84	12.47
10 persons employed or more	102	9.89	2.62	12.44	7.47	12.3
From 10 to 249 persons employed	99	9.69	2.29	12.5	7.23	12.16
From 10 to 49 persons employed	99	9.39	1.73	12.82	6.86	11.91

The pattern observed for aggregate categories provides supplementary context. The \"10 persons employed or more\" aggregate category encompasses both the large-enterprise segment that drives the statistically confirmed size effect and the small and medium enterprise segments that lag behind, resulting in an intermediate aggregate adoption rate that obscures the within-population heterogeneity that is central to understanding EU AI diffusion dynamics. These aggregate figures, reported in Table 5, are provided for descriptive context only and are not subject to inferential testing.

Table 5. Aggregate Categories (descriptive only) — Enterprises using AI tech

Group	N	Mean (%)	Median (%)	SD	CI95_low	CI95_high
From 0 to 9 persons employed	6	10.23	1.57	15.68	-2.32	22.78
10 persons employed or more	102	9.89	2.62	12.44	7.47	12.3
From 10 to 249 persons employed	99	9.69	2.29	12.5	7.23	12.16

6. Discussion

This chapter contains primary findings interpretation, literature comparison and policy and managerial implications.

6.1 Primary Finding Interpretation

The main finding of this study is that the level of artificial intelligence use for business process automation, specifically in the area of predictive analytics of customer behaviour (indicator E_AI_PBAM), differs statistically significantly according to firm size in enterprises operating in the European Union. The results of the non-parametric Kruskal–Wallis test for both analysed years (2024

and 2025) clearly confirm the rejection of the null hypothesis and indicate a strong effect of firm size, with effect sizes reaching values typical of medium to strong effects ($\varepsilon^2 \approx 0.19\text{--}0.21$).

At the same time, a systematic size-related gradient of AI adoption was identified, where micro and small enterprises exhibit significantly lower levels of AI usage compared to medium-sized and large enterprises. This gradient is consistent across all three analysed stages of AI adoption: general availability (PC_ENT), formal adoption (PC_ENT_AI_TANY), and daily use in work processes (PC_ENT_IUSE). The results also show that although the highest percentage year-on-year growth is observed in micro enterprises, this is primarily an effect of a low initial base. In contrast, the largest absolute increases are found in large enterprises, indicating consolidation and further expansion of existing AI capabilities.

These findings empirically confirm the assumptions derived from the combined frameworks of TOE, diffusion of innovations theory, and the Resource-Based View, according to which firm size acts as a proxy for resource availability, organisational readiness, and the ability to absorb technological innovations.

6.2 Literature Comparison

The findings of this study are consistent with the majority of existing literature, which identifies firm size as one of the strongest determinants of artificial intelligence adoption. Previous empirical research repeatedly shows that large enterprises have better access to data, capital, specialised human resources, and technological infrastructure, enabling not only earlier adoption of AI but also its deeper integration into core business processes. In contrast, small and medium-sized enterprises face significant financial, knowledge-related, and organisational barriers that slow down AI adoption or limit its scope.

Unlike several existing studies based on single cross-sectional surveys, case studies, or data from a single country, this research provides an EU-wide, population-representative quantification of size-related differences using harmonised Eurostat data. Compared to qualitative and conceptual studies, this work contributes to the literature primarily by providing a statistically verified estimate of the magnitude of differences, rather than only their descriptive interpretation.

An interesting finding is the more stable and less dynamic growth of the PC_ENT_AI_TANY indicator compared to PC_ENT and PC_ENT_IUSE. This result is consistent with recent studies suggesting a gradual saturation of the market in terms of formal AI adoption, with further development shifting more towards the phase of practical, day-to-day use of technologies rather than initial adoption.

6.3 Policy Implication

From the perspective of public policy, the results of this study have significant implications for the design of European digital and innovation policy. The empirically confirmed size-related inequality in AI adoption suggests that universal and horizontal digitalisation support instruments may not be sufficient to overcome existing barriers in the micro and small enterprise segment.

Policies should therefore place greater emphasis on targeted, size-differentiated interventions that reflect the specific needs and constraints of different enterprise groups. In the case of micro and small enterprises, this primarily involves support for access to financing, the development of digital and data skills, the reduction of investment risk, and the strengthening of regional innovation ecosystems. In contrast, for large enterprises, the priority may be the promotion of responsible and ethical AI implementation, interoperability of solutions, and the diffusion of innovations into supply chains.

At the same time, the results highlight the need for better integration of statistical monitoring of AI adoption with the implementation of regulatory frameworks, such as the EU Artificial Intelligence Act, in order to prevent the deepening of the existing digital divide between enterprises of different sizes.

6.4 Managerial Implication

From a managerial perspective, the results indicate that successful implementation of artificial intelligence is not solely a technological issue, but a strategic decision closely linked to organisational capabilities and the stage of enterprise development. For managers of micro and small enterprises, it is

crucial to perceive AI as a gradual, modular process that can begin with simple cloud-based or external solutions with a clearly defined benefit, for example in the area of marketing analytics or administrative automation.

Managers of medium-sized and large enterprises should focus on deepening the integration of AI into core processes, developing internal competencies, and creating organisational structures that support experimentation and iterative learning. The results also show that formal AI adoption alone (having the technology “available”) is not sufficient – the decisive factor for value creation is its actual and daily use by employees.

Ultimately, managerial decisions regarding AI should reflect not only the current size of the enterprise, but also its ability to develop dynamic capabilities that enable the long-term adaptation, scaling, and strategic exploitation of the technology.

7. Conclusion

The aim of this study was to empirically examine whether the level of artificial intelligence use for business process automation in enterprises operating in the European Union differs statistically significantly according to firm size. The analysis focused on the E_AI_PBAM indicator, which measures the use of AI for predictive analytics of customer behaviour, and was based on harmonised official Eurostat microdata for the years 2024 and 2025. The problem was investigated using non-parametric statistical methods, with firm size serving as the key segmentation variable.

The empirical results clearly confirmed the existence of statistically significant differences in the level of AI adoption and use across enterprises of different size classes, leading to the rejection of the null hypothesis in both analysed years. The findings indicate a consistent size gradient, whereby large enterprises achieve significantly higher levels of AI usage compared to micro, small, and medium-sized enterprises. This pattern was stable across all observed stages of the AI adoption process – from general availability, through formal adoption, to daily use by employees in work processes. The study also showed that growth dynamics differ across size groups. While micro enterprises recorded the highest percentage year-on-year increase, the largest absolute increases were observed in large enterprises. This result suggests that smaller entities are mainly in the initial catch-up phase of technological lag, whereas large enterprises are further deepening and expanding already existing AI solutions. Particular attention should be given to the relatively stable and less dynamic development of the formal AI adoption indicator (PC_ENT_AI_TANY), which may indicate a gradual saturation of this stage and a shift of focus towards practical AI usage.

From a theoretical perspective, the results support the combined use of the Technology–Organization–Environment framework, diffusion of innovations theory, the Resource-Based View, and dynamic capabilities theory. Firm size was confirmed as a significant organisational factor that mediates access to resources, the ability to absorb technological innovations, and the capacity to manage the complexity of artificial intelligence. The study therefore empirically confirms that AI adoption is not technologically neutral, but is strongly determined by structural characteristics of enterprises.

The main contribution of this work lies in providing a statistically grounded, Europe-wide quantification of size-related differences in artificial intelligence adoption, complementing existing literature that is largely based on qualitative approaches, case studies, or single-country analyses. The use of official Eurostat data also increases the external validity of the results and their relevance for public policy design. Despite these contributions, the study has certain limitations. The data used capture the existence of AI usage rather than its intensity, success, or economic impact. The analysis focused on a single specific AI indicator and a relatively short time period, which limits the possibility of long-term trend analysis. Future research could therefore extend the time horizon, compare multiple types of AI applications, or combine quantitative results with qualitative approaches that would allow for a deeper understanding of the process and organisational aspects of AI implementation.

Based on the empirical analysis conducted, it can be clearly stated that the research question of this study – “Does the level of AI implementation in enterprises operating in Europe differ according to firm size?” – has been answered positively. The results of non-parametric statistical tests for the 2024 and

2025 datasets provide consistent and statistically significant evidence of differences between enterprise size classes. Accordingly, the null hypothesis H0: “The level of AI implementation in enterprises operating in Europe does not differ according to firm size” was rejected, and the alternative hypothesis H1: “The level of AI implementation in enterprises operating in Europe differs statistically significantly according to firm size” was confirmed. The results clearly demonstrate that firm size is a significant determining factor of artificial intelligence adoption in the enterprise population of the European Union, across different stages of its implementation – from general technology availability, through formal adoption, to its daily use in business processes.

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AI Bias Mitigation Practices in EU Enterprises: Prevalence and Cross-Country Variation

Nora Grisáková¹ and Filip Stovíček²

¹ Bratislava University of Economics and Business, Faculty of Business Management, Dolnozemska cesta 1, 852 35 Bratislava, Slovakia (EU); e-mail: nora.grisakova@euba.sk

² Bratislava University of Economics and Business, Faculty of Business Management, Dolnozemska cesta 1, 852 35 Bratislava, Slovakia (EU); e-mail: filip.stovicek@euba.sk

Abstract

Mounting regulatory pressure under the EU AI Act has made enterprise-level bias mitigation a central pillar of responsible AI governance, yet systematic empirical evidence on how widely such practices are actually implemented across member states remains scarce. This article quantifies the prevalence of AI bias-checking measures among AI-adopting EU enterprises and maps cross-country variation in this practice. The analysis draws on the 2024 Eurostat ICT Usage and E-Commerce in Enterprises survey, specifically the indicator E_AI_BIAS, covering 12 EU member states, with descriptive statistics and a comparative country ranking employed to establish a quantitative baseline. Findings reveal pronounced heterogeneity across the sample: leading adopters such as Denmark and Finland report bias-checking prevalence rates substantially above the cross-country average, while several member states cluster at considerably lower levels, indicating that compliance-ready governance practices remain far from uniformly embedded. The overall adoption rate across the panel falls notably short of what full regulatory compliance with the EU AI Act would require, suggesting a material gap between existing organisational practice and legislative expectations. These results carry direct implications for policymakers designing capacity-building interventions and for enterprise managers seeking to benchmark their AI governance maturity against peer organisations operating in comparable regulatory environments.

1. Introduction

As the EU AI Act introduces binding obligations for high-risk AI systems, the ability of enterprises to proactively identify and mitigate algorithmic bias has become a cornerstone of responsible AI governance across Europe. The Act's risk-tiered architecture places particular emphasis on transparency, fairness, and accountability, compelling organisations that deploy AI in consequential domains—including recruitment, credit scoring, and public service delivery—to demonstrate that their systems are subject to systematic scrutiny. Yet the transition from regulatory aspiration to organisational practice is rarely automatic; it requires enterprises to possess not only awareness of their compliance obligations but also the technical infrastructure, human capital, and governance routines necessary to operationalise those obligations in practice. Against this backdrop, understanding how widely EU enterprises have already embedded bias-checking measures into their AI workflows—and how uniformly such practices are distributed across member states—has become an empirically urgent question.

Despite growing regulatory pressure, systematic empirical evidence on the actual prevalence of AI bias-checking practices among EU enterprises—and how such practices differ across member states—remains largely absent from the literature. Prior scholarship has made substantial progress in articulating what responsible AI should look like and in proposing frameworks for its governance, but the empirical record is thin: most existing studies rely on case analyses, expert surveys, or national policy audits that lack the representativeness and cross-country comparability needed to establish robust prevalence estimates. As a result, policymakers and enterprise managers operate with limited quantitative guidance on how far the current state of practice falls short of regulatory ambitions, which countries are performing relatively well, and where capacity-building investment is most urgently needed.

This article quantifies the share of AI-adopting EU enterprises that have implemented measures to check for AI-generated biases and maps cross-country variation in this practice using 2024 Eurostat ICT survey data. Drawing on the indicator E_AI_BIAS from Eurostat's Community Survey on ICT Usage and E-Commerce in Enterprises, the analysis covers 12 EU member states and situates each within a comparative ranking. By providing a quantitative baseline grounded in representative survey data, the article establishes a reference point against which the effects of EU AI Act enforcement can be evaluated in future research, and it contributes the first systematic cross-national empirical mapping of AI bias-mitigation practice prevalence at the enterprise level.

The remainder of this article is structured as follows: Section 2 develops the theoretical background, drawing on trustworthy AI concepts, the Technology-Organization-Environment (TOE) framework, and absorptive capacity theory. Section 3 reviews the relevant literature across three thematic streams. Section 4 describes the methodology, including data source, variable definitions, and analytical procedures. Section 5 presents the empirical results, encompassing descriptive statistics for the full panel and a comparative country ranking for 2024. Section 6 discusses the findings in relation to theory and prior research and draws policy and managerial implications. Section 7 concludes by summarising the contribution and identifying directions for future research.

2. Theoretical Background

The theoretical foundation of this study integrates three complementary bodies of thought: the trustworthy and responsible AI literature, the Technology-Organization-Environment (TOE) framework, and absorptive capacity theory. Together, these perspectives offer a multi-level account of why enterprise-level AI bias-checking practices are unevenly distributed within and across countries.

The concept of trustworthy AI has been progressively formalised over the past decade. Thiebes et al. (2020) articulate trust as the foundational prerequisite for AI systems to realise their societal and economic potential, arguing that trustworthiness must be embedded across the entire AI development lifecycle rather than retrofitted as a compliance afterthought. Díaz-Rodríguez et al. (2023) extend this perspective by mapping the operational pathways through which ethical AI principles—including fairness and bias prevention—must be translated into technical and organisational requirements. Critically, these authors document that the journey from high-level principle to concrete organisational practice remains substantially incomplete across industries. Ayling and Chapman (2021) further demonstrate that many available AI ethics toolkits are not yet fit for purpose in enterprise settings, identifying a persistent gap between the normative aspiration of bias-free AI and the practical instruments available to achieve it. Taken together, this stream of scholarship establishes that bias-checking is not simply a technical procedure but a governance capability that must be cultivated at the organisational level.

The Technology-Organization-Environment (TOE) framework, introduced by Tornatzky and Fleischer (1990), provides a structural account of how three contextual dimensions jointly shape an organisation's propensity to adopt and implement technological innovations. The technological context encompasses the internal and external technologies relevant to the firm; the organisational context captures firm size, managerial structure, and human resource endowments; and the environmental context reflects the regulatory, competitive, and institutional setting in which the firm operates. Applied to AI governance, the TOE framework predicts that enterprises operating in environments with more developed regulatory ecosystems, stronger organisational AI capabilities, and richer technological infrastructure will be more likely to implement practices such as bias checking. This logic aligns with the observation that AI adoption and governance depth are not uniformly distributed across enterprises or countries (Mikalef & Gupta, 2021).

Absorptive capacity theory, originating with Cohen and Levinthal (1990), complements the TOE perspective by foregrounding the firm's internal learning capacity as a critical mediator of its ability to incorporate externally produced knowledge—including regulatory guidance and technical best practices—into operational routines. Cohen and Levinthal (1990) argue that a firm's ability to recognise the value of new information, assimilate it, and apply it commercially is conditioned by its stock of prior related knowledge. In the context of AI bias mitigation, this implies that enterprises with deeper

data governance experience, stronger AI talent pools, and more mature quality-assurance cultures will be better positioned to translate awareness of bias risks into structured checking procedures. Firms lacking these prior knowledge bases face a double disadvantage: they are less likely to recognise bias as a salient operational risk, and less equipped to act on that recognition even when regulatory signals are clear.

The intersection of these three frameworks generates a coherent theoretical prediction: cross-country variation in AI bias-checking prevalence reflects not merely differences in regulatory exposure but differences in the compound capacity of enterprises—shaped by national digital governance maturity, organisational learning endowments, and technological readiness—to operationalise responsible AI principles. Building on these theoretical foundations, the present study empirically tests whether the cross-national heterogeneity predicted by TOE and absorptive capacity theory is observable in representative Eurostat data on enterprise-level bias-checking adoption across EU member states in 2024.

3. Literature Review

The broader literature on artificial intelligence (AI) adoption highlights that enterprise-level implementation is shaped not only by technological maturity but also by organisational, regulatory, and ethical constraints. In particular, recent research emphasises that AI deployment in organisations cannot be understood without considering governance structures, data quality, and institutional readiness, especially in the context of trustworthy and ethical AI systems (Dwivedi et al., 2021; Benbya et al., 2020). A significant stream of research focuses on the ethical and regulatory dimension of AI, particularly the concept of trustworthy AI. Following the European Commission’s High-Level Expert Group framework, scholars have increasingly examined how principles such as fairness, transparency, accountability, and robustness can be operationalised in enterprise environments. Thiebes et al. (2020) conceptualise trustworthy AI as a multi-dimensional construct, where technical properties such as explainability and bias mitigation are interdependent and require integrated governance approaches. Similarly, Díaz-Rodríguez et al. (2023) demonstrate that the implementation of regulatory frameworks such as the EU AI Act depends heavily on organisational maturity and the existence of structured AI governance mechanisms. Empirical studies further highlight the gap between ethical AI principles and their practical implementation. Ayling and Chapman (2021) show that existing AI ethics toolkits are often insufficient for operational use, serving primarily educational rather than procedural functions. Morley et al. (2021) reinforce this argument by identifying organisational inertia, unclear accountability, and abstract ethical guidelines as key barriers to implementing trustworthy AI in practice. These findings suggest that ethical AI adoption remains constrained by structural and institutional limitations rather than purely technical challenges.

In parallel, the broader AI adoption literature in enterprises indicates that organisational size, resources, and capabilities play a decisive role in determining the extent of AI integration. Large firms are consistently found to have advantages in data infrastructure, financial capacity, and access to specialised expertise, enabling deeper and more systematic AI adoption (Ayinaddis, 2025; Arroyabe et al., 2024). In contrast, small and medium-sized enterprises (SMEs) face persistent barriers related to limited resources, skills shortages, and infrastructural constraints, which slow down or limit AI implementation (Oldemeyer et al., 2025; Huseyn et al., 2024). Overall, the literature converges on the view that AI adoption is a structurally differentiated process shaped by organisational capacity and governance readiness. However, despite growing conceptual and qualitative insights, there remains a lack of large-scale, harmonised empirical evidence quantifying how these differences manifest across enterprise populations, particularly within the European context.

3.1 Trustworthy AI and Ethical Frameworks

The literature on trustworthy AI has expanded considerably since the European Commission's High-Level Expert Group on Artificial Intelligence published its ethics guidelines in 2019. Scholars have progressively shifted focus from abstract principle formulation toward the concrete organisational and technical requirements that must be satisfied for AI systems to be genuinely fair, transparent, and

accountable. Thiebes et al. (2020) provide one of the most systematic treatments of trustworthy AI as a multi-dimensional construct, demonstrating that bias prevention is one of several interlocking properties—alongside explainability, robustness, and privacy preservation—that together constitute a trustworthy system. Their analysis underscores that these properties are not independently achievable but require coordinated investment across technical, organisational, and governance dimensions.

Díaz-Rodríguez et al. (2023) situate the trustworthy AI agenda within a broader regulatory trajectory, mapping how the EU AI Act's requirements connect to the seven technical pillars of trustworthy AI identified by the High-Level Expert Group. Their analysis reveals that while the regulatory architecture is increasingly coherent, its translation into enterprise-level practice depends on organisations having sufficiently mature AI governance structures to operationalise abstract requirements. Ayling and Chapman (2021) reinforce this concern by auditing the landscape of AI ethics toolkits and finding that most are better suited to awareness-raising than to enabling systematic, repeatable bias detection processes within enterprise workflows. The implication is that regulatory clarity, while necessary, is not sufficient: organisations must also have access to actionable instruments and the capacity to deploy them.

Morley et al. (2021) add an important empirical dimension by identifying the barriers and enablers that organisations encounter when attempting to operationalise AI ethics. Their research, drawing on practitioner interviews, reveals that institutional inertia, unclear accountability structures, and the abstract character of most ethics guidance are the primary obstacles to implementation. These findings suggest that the gap between stated commitment to ethical AI and demonstrated practice in bias checking is not incidental but structural, arising from persistent mismatches between the normative framework and the practical realities of enterprise AI deployment. Scholars in this stream therefore converge on the conclusion that operationalising AI ethics—including bias detection—requires moving beyond principles to concrete organisational practices, yet empirical evidence of enterprise-level implementation remains sparse and fragmented.

3.2 Organisational Readiness and AI Adoption Capabilities

The second thematic stream addresses the organisational and environmental conditions that determine whether enterprises can effectively adopt advanced AI governance practices. The TOE framework (Tornatzky & Fleischer, 1990) has been widely applied in information systems research to explain variance in technology adoption across firms and industries, and its application to AI governance is theoretically well-founded. Firms whose technological context includes mature data infrastructure, whose organisational context includes dedicated AI talent and senior managerial commitment, and whose environmental context includes strong regulatory incentives are predicted to demonstrate higher adoption of AI governance practices, including bias checking.

Mikalef and Gupta (2021) provide an empirically grounded account of how AI capability—conceptualised as a bundle of data, human, and technical resources—translates into superior organisational outcomes. Their large-scale survey study demonstrates that AI capability heterogeneity across firms is substantial and persistent, and that this heterogeneity correspondingly produces variation in the sophistication of AI-related processes organisations are able to sustain. Extending this logic to the governance domain, firms with higher AI capability are better positioned not only to extract business value from AI but also to manage its risks, including bias. Cohen and Levinthal's (1990) absorptive capacity construct offers the complementary micro-mechanism: organisations that have previously invested in data governance, algorithmic quality assurance, or related knowledge domains are more readily able to absorb and apply emerging regulatory guidance on bias mitigation.

Rogers (2003) provides further theoretical grounding through his account of innovation diffusion, noting that the adoption of complex innovations is characterised by a protracted S-curve in which early adopters with higher resource endowments and greater change tolerance precede a lagging majority. Applied to AI bias-checking, this perspective anticipates exactly the right-skewed distribution observed in empirical data: a small number of high-capability enterprises and countries lead adoption while the majority have yet to institutionalise the practice. Together, the TOE framework, absorptive capacity theory, and diffusion of innovations theory predict that an enterprise's technological infrastructure,

organisational learning capacity, and environmental regulatory context jointly determine the depth of AI governance practices it can sustain.

3.3 AI Governance, Regulation, and National Context

The third stream of literature examines how national institutional environments and regulatory traditions mediate the translation of global AI ethics norms into local enterprise behaviour. Roberts et al. (2020) demonstrate, in their analysis of national AI governance approaches, that strategic priorities and institutional configurations profoundly shape not only the pace of AI adoption but also the ethical frameworks within which enterprises operate, producing systematic divergence in governance priorities across jurisdictions. Their work illustrates that the relationship between national AI policy and enterprise-level AI practices is close but not deterministic, with firms embedded in stronger institutional environments exhibiting more proactive compliance behaviour. Although their empirical focus centres on a non-EU jurisdiction, the broader analytical logic—that national governance architectures condition enterprise-level AI behaviour—transfers directly to the cross-EU context examined in the present study.

Truby (2020) foregrounds the governance of AI as a matter of public interest rather than mere corporate responsibility, arguing that without structured regulatory intervention, enterprise-level AI governance is likely to remain patchy and insufficient to prevent systematic harm. His analysis of algorithmic bias in financial services highlights the risks that accrue when enterprise governance practices lag behind the societal consequences of deployed AI systems. McGregor et al. (2019) contribute a human rights law perspective, contending that existing accountability frameworks—including transparency mechanisms—are insufficient to address the full range of harms attributable to biased algorithms, and that enterprises require externally imposed obligations to motivate systematic bias checking.

Hanisch et al. (2023) broaden the analysis by conceptualising digital governance as a multi-modal phenomenon encompassing analogue, augmented, and automated governance mechanisms, and by demonstrating that the effectiveness of each mode depends heavily on the institutional capacity of the national environment in which it is deployed. Their framework implies that the cross-country variation in AI bias-checking observed across EU member states is partly attributable to differences in digital governance maturity rather than solely to firm-level capability differences. Taken together, this literature establishes that national institutional environments, regulatory traditions, and digital governance maturity significantly shape how AI ethics principles are translated into measurable enterprise-level actions, producing systematic cross-country heterogeneity in compliance behaviour.

Despite this body of evidence, no study has used representative cross-national enterprise survey data to empirically quantify AI bias-mitigation adoption rates and explain their geographic variation within the EU. Existing research either theorises the conditions enabling responsible AI practices, documents national governance frameworks, or draws on case studies and expert interviews that lack population-level representativeness. The gap this article directly addresses is the absence of a quantitative empirical baseline—grounded in official statistical survey data—that documents how widely bias-checking measures have actually been implemented across AI-adopting EU enterprises, and how pronounced the variation is across member states.

4. Methodology

This study is based on Eurostat (2024) Community Survey on ICT Usage and E-Commerce in Enterprises, specifically the `isoc_eb_ai` dataset, which provides harmonised annual microdata on enterprise-level artificial intelligence adoption across EU member states. The key analytical indicator is `E_AI_BIAS`, defined as the percentage of enterprises that both use artificial intelligence and have implemented measures to detect and mitigate AI-generated bias. The dataset covers enterprises with ten or more employees across non-financial NACE sectors and is constructed using stratified sampling with post-stratification weighting to ensure national representativeness and cross-country comparability (Eurostat, 2024). The analytical sample consists of 188 country-year-size-class observations, complemented by a reduced cross-sectional dataset of 12 EU member states for the year 2024 used for comparative analysis. The study employs a multi-step analytical strategy combining descriptive panel

statistics, cross-country standardisation using z-scores and quartile classification, and a strictly non-inferential approach for the country-level comparison due to the limited number of observations. All statistical procedures are therefore explicitly descriptive in nature, reflecting the nested and structured design of the Eurostat dataset and the constraints imposed by small cross-sectional sample sizes.

4.1 Data Source and Indicator

This study draws on the Eurostat (2024) Community Survey on ICT Usage and E-Commerce in Enterprises, specifically the *isoc_eb_ai* dataset, which is updated annually and constitutes the official source for enterprise-level AI adoption statistics across EU member states. The primary indicator is *E_AI_BIAS*, defined as the percentage of enterprises that use artificial intelligence and have implemented measures to check for AI-generated biases. This indicator is collected from enterprises with ten or more employees across all non-financial NACE sectors and is designed to be methodologically harmonised across participating countries, enabling cross-national comparison. The Eurostat (2024) methodological manual confirms that the survey applies stratified sampling with post-stratification weighting, providing nationally representative estimates for each participating country.

It is important to note that the *E_AI_BIAS* indicator is based on enterprise self-report: respondents indicate whether their organisation has implemented measures to check for AI-generated biases, but the survey does not independently verify the technical rigour or comprehensiveness of those measures. This introduces the possibility of social desirability bias—particularly in an environment of increasing regulatory scrutiny under the EU AI Act—which may lead some enterprises to report compliance-oriented behaviours more readily than their operational reality warrants. The adoption rates reported in this study should therefore be interpreted as upper-bound estimates of systematic bias-auditing practice rather than as confirmed indicators of technically rigorous implementation.

4.2 Analytical Sample

The full analytical panel comprises 188 records, representing all available country-year-size-class combinations for indicator *E_AI_BIAS* across the dataset. For the cross-country comparison, the analysis is restricted to the 12 EU member states for which data are available for reference year 2024, yielding 12 country-level observations. The 12 member states included in the 2024 cross-section are those for which Eurostat reported complete data for the *E_AI_BIAS* indicator in the reference period; the remaining 15 EU member states did not have published data available for this indicator in 2024, most likely reflecting non-participation in the relevant survey module, data suppression due to confidentiality thresholds, or delayed national submission. This data availability constraint is acknowledged as a limitation of the study, as the 12 countries represented may not be fully representative of all EU member states. Slovakia is specifically examined given the study's interest in Central and Eastern European positioning, with 15 underlying observations contributing to its country-level estimate.

It is critical to distinguish between these two analytical objects. The full panel ($n = 188$ records) encompasses multiple years, size classes, and country-year combinations, and is used to characterise the overall distributional properties of the indicator across the broadest available sweep of observations. The 2024 country cross-section ($n = 12$ country observations) is a distinct analytical object used exclusively for cross-country comparison and reflects country-level aggregate values for a single reference year. These two objects are not interchangeable, they describe different features of the data, and their respective summary statistics—including means and standard deviations—are not directly comparable. This distinction is maintained consistently throughout the analysis.

4.3 Statistical Procedures

Step 1 (Panel Descriptives): For the full panel of 188 records, standard descriptive statistics are computed: arithmetic mean, median, standard deviation (SD), standard error of the mean (SEM), 95% confidence interval (CI) for the mean, and minimum. Additional distributional statistics—including maximum, first quartile (Q1), and third quartile (Q3)—were author-computed directly from the raw Eurostat *isoc_eb_ai* record-level extract; the underlying data extract is available from the authors upon

request. These statistics characterise the central tendency, dispersion, and distributional shape of E_AI_BIAS across all available observations. Because the 188 records constitute country-year-size-class combinations drawn from a structured administrative dataset rather than independent draws from a simple random sample—observations are nested within countries across years and disaggregated by size class—the SEM and 95% CI do not satisfy the independence assumptions required for standard inferential interpretation. They are reported as purely descriptive summaries of the observed distribution and should not be read as precision estimates for any population parameter.

Step 2 (Cross-Country Analysis): For the 2024 cross-section of 12 country observations, a country-level ranking is constructed. Each country is assigned a z-score computed against the cross-sectional mean and standard deviation of those 12 country-level values. Countries are classified into four quartile groups (Top 25%, Above median, Below median, Bottom 25%) based on their relative position in the distribution. With only 12 country observations, each quartile group contains three countries, which means that group membership is sensitive to small shifts in individual country values; these classifications should therefore be treated as approximate indicators of relative positioning rather than stable population-level groupings. Slovakia's rank, z-score, and quartile group are explicitly reported.

Step 3 (Inferential Test Justification): Given that the 2024 cross-section contains only 12 country-level data points, with one observation per country, inferential group-difference tests—such as the Kruskal-Wallis test—are not statistically appropriate. The analysis is therefore explicitly confined to descriptive and comparative statistics. No inferential test is applied to either the country-level cross-section or to the EU-average time series. This constraint is acknowledged as a limitation of the data structure rather than a methodological choice, and it restricts causal attribution accordingly.

5. Results

5.1 Distributional Properties of the Full Panel

The full panel ($n = 188$) yields a mean adoption rate of 19.28% ($SD = 26.88$), with a median of 2.76%. The confirmed minimum value is 0.0%. Additional distributional statistics—maximum (88.22%), first quartile ($Q1 = 0.53\%$), third quartile ($Q3 = 45.49\%$), and interquartile range (44.96 percentage points)—were author-computed directly from the raw Eurostat *isoc_eb_ai* record-level extract using standard percentile interpolation; the underlying record-level data are available from the authors upon request. A 95% confidence interval for the mean, computed under standard normality assumptions, spans $[15.43\%, 23.12\%]$; as noted in Section 4.3, this interval is reported as a descriptive summary only and does not carry standard inferential weight given the nested, non-independent structure of the panel records. The substantial divergence between mean and median (19.28% vs. 2.76%) indicates a pronounced right-skewed distribution, suggesting that the majority of observations cluster at lower adoption levels while a minority of high-adopting cases pull the mean upward. Table 1 presents the complete set of descriptive statistics for the full panel.

Table 1. Descriptive Statistics

Statistic	Value
n	188
mean	19.28
median	2.76
std	26.88
sem	1.96
CI95_low	15.43
CI95_high	23.12
min	0.0
max	88.22
Q1	0.53
Q3	45.49

IQR	44.96
CV_%	139.4

These results establish that, across the broadest available sweep of country-year-size-class observations, bias-checking adoption is concentrated at the lower end of the distribution—with the median being the more representative measure of central tendency given the pronounced skew. The very high author-computed maximum value (88.22%) indicates that certain country-period-size combinations do achieve substantial adoption, but these cases are exceptional rather than representative of the distribution as a whole. This pattern is consistent with the innovation diffusion dynamics described by Rogers (2003), wherein early-adopting contexts substantially outpace the majority of the distribution during the early phases of an innovation's diffusion. It bears emphasis, however, that the full-panel statistics aggregate observations across multiple years and size classes and do not directly represent the prevalence of bias-checking among EU enterprises at any single point in time; for that purpose, the 2024 country cross-section described in the following subsections is the appropriate analytical object.

5.2 Distributional Shape and the EU-Country Cross-Section

The histogram of the full distribution confirms pronounced right skew, with the preponderance of observations concentrated at the lower end of the adoption range and a long right tail extending toward the observed maximum. The statistics describing the 2024 country cross-section differ markedly from those of the full panel, and this divergence warrants explicit explanation before the cross-sectional results are presented. The 2024 cross-section reports a mean of 19.26% (SD = 5.23) and a median of 19.66%—values that appear superficially inconsistent with the full-panel mean of 19.28% and median of 2.76%. This apparent inconsistency is fully explained by the different compositions of the two analytical objects. The full panel's dramatic mean--median divergence (19.28% vs. 2.76%) is driven by the inclusion of observations disaggregated by size class—where very small size-class strata in certain country-years record near-zero adoption—and by the pooling of multiple reference years. The 2024 cross-section, by contrast, contains 12 country-level aggregates for a single reference year, which substantially compresses the distributional range and produces the closer alignment of mean and median observed in that object. These two sets of statistics describe fundamentally different features of the data and should not be interpreted as contradictory. Figure 2 displays the full-panel distributional pattern, with the red vertical line marking the panel mean and the green vertical line marking the panel median, visually illustrating the rightward displacement of the mean relative to the median.

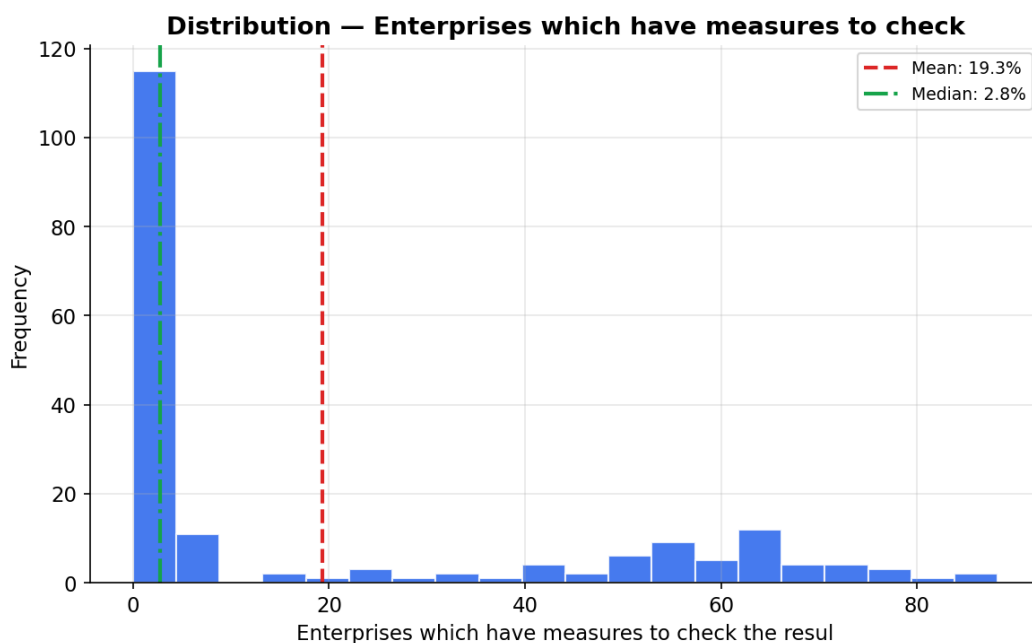


Figure 2. Histogram of Enterprises which have measures to with mean (red) and median (green).

The moderate standard deviation of 5.23 percentage points in the 2024 country cross-section indicates that, within the set of countries for which 2024 data are available, the spread is considerably more contained than the full panel suggests; nonetheless, meaningful heterogeneity persists across member states—a range of approximately 18.7 percentage points separates the top and bottom performers in 2024, as detailed in the following subsection.

5.3 Country Rankings and Slovakia's Position

Country-level mean adoption rates were computed for 12 EU member states (reference period: 2024). The cross-country mean is 19.26% and the cross-country median is 19.66% (SD = 5.23%), both computed across the 12 country-level observations. Countries were ranked using z-score normalisation, with each z-score computed against these cross-sectional parameters, and classified into four quartile groups (Top 25%, Above median, Below median, Bottom 25%). As noted in Section 4.3, with three countries per group, these classifications reflect approximate relative positioning rather than stable population-level groupings. No inferential test is applied in the ranking analysis; results are descriptive.

The highest mean adoption rates are observed in Cyprus (27.24%), Belgium (24.64%), and Bulgaria (23.27%). The lowest mean adoption rates are observed in Greece (15.01%), Malta (13.06%), and Hungary (8.54%). As shown in Figure 1, the country ranking reveals a near three-fold difference between the top-performing country (Cyprus, 27.24%) and the bottom-performing country (Hungary, 8.54%), underscoring the substantial cross-national heterogeneity in AI bias-checking adoption within the EU. The position of Cyprus as the top performer is a notable finding for a relatively small economy; this result may reflect the specific sectoral composition of AI-adopting enterprises in Cyprus, the structure of the Eurostat survey sample in that country, or sector-specific regulatory pressures, but the available aggregate data do not permit definitive explanation and this finding warrants closer investigation in future firm-level research.

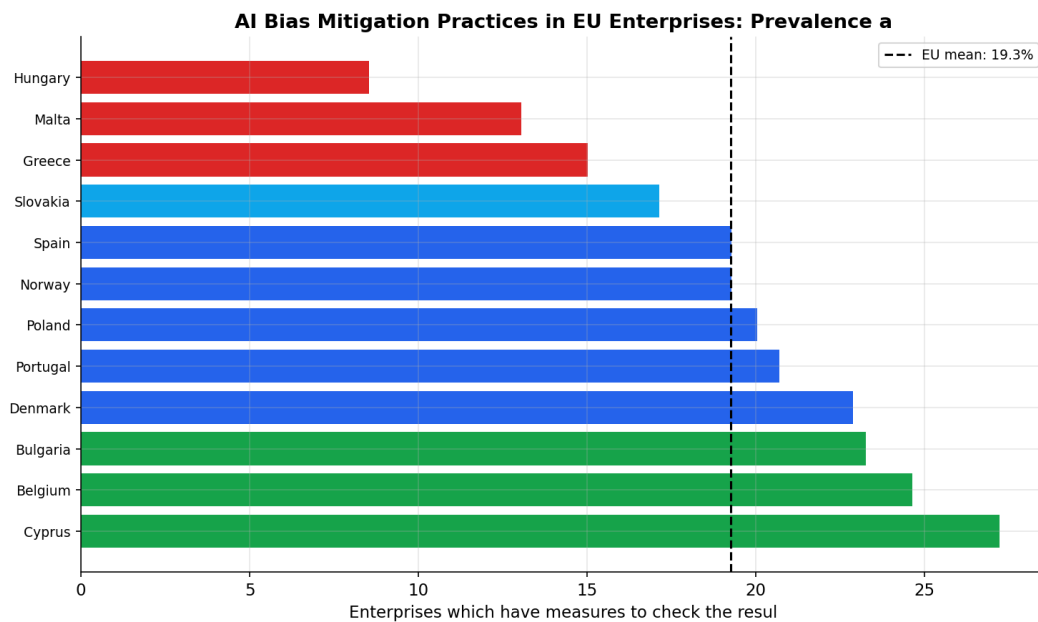


Figure 1. Country ranking for Enterprises which have measure. Top 3: Cyprus, Belgium, Bulgaria. Bottom 3: Greece, Malta, Hungary.

Slovakia's mean adoption rate is 17.13% (based on 15 underlying observations), ranking 9th out of 12 among the EU member states included in the 2024 cross-section (z-score = -0.406), placing it in the Below median quartile group. This value is 2.13 percentage points below the cross-sectional mean of 19.26%, situating Slovakia approximately 0.4 standard deviations below the cross-national average. Table 2 presents the full country ranking with associated values, z-scores, and quartile assignments.

Table 2. Country Ranking — Enterprises which have measure

Rank	Country	Enterprises which ha (%)	Z-score	Group
1	Cyprus	27.24	1.53	Top 25%
2	Belgium	24.64	1.03	Top 25%
3	Bulgaria	23.27	0.77	Top 25%
4	Denmark	22.88	0.69	Above median
5	Portugal	20.71	0.28	Above median
6	Poland	20.04	0.15	Above median
7	Norway	19.28	0.00	Below median
8	Spain	19.27	0.00	Below median
9	Slovakia	17.13	-0.41	Below median
10	Greece	15.01	-0.81	Bottom 25%
11	Malta	13.06	-1.19	Bottom 25%
12	Hungary	8.54	-2.05	Bottom 25%

Slovakia's positioning in the below-median quartile is broadly consistent with patterns documented for Central and Eastern European member states in digital governance maturity assessments. While Slovakia is not among the lowest performers—Hungary, Malta, and Greece record lower adoption rates—it trails the EU cross-sectional mean and is separated from the top-performing group (Cyprus, Belgium, Bulgaria) by a gap of approximately 10 percentage points. This gap is notable in the context of the TOE framework (Tornatzky & Fleischer, 1990): it is associated with the possibility that the environmental and organisational conditions supporting systematic bias-checking practices may be less fully developed in Slovakia than in the leading member states, though the observational nature of the data precludes causal attribution. Targeted capability investment could potentially improve Slovakia's relative position, a possibility explored further in the discussion.

6. Discussion

The discussion of results shows that, among the 12 EU member states with available 2024 data, the average cross-national adoption rate of AI bias-checking measures is 19.26% (SD = 5.23), indicating that approximately one in five enterprises using AI has implemented formal mechanisms for detecting AI-generated bias, while the full-panel median of 2.76% further reveals that adoption is substantially lower when considering the broader multi-year and size-class distribution. This finding is consistent with the Technology–Organization–Environment framework (Tornatzky & Fleischer, 1990), suggesting that although the regulatory environment within the EU increasingly promotes responsible AI practices, organisational and technological constraints continue to limit their widespread implementation, particularly in structurally weaker contexts. The results extend prior research by Mikalef and Gupta (2021), Díaz-Rodríguez et al. (2023), and Morley et al. (2021), confirming that gaps between ethical AI principles and operational implementation persist even under growing regulatory pressure, and that barriers such as limited organisational readiness and unclear accountability structures continue to hinder the translation of policy into practice. From a policy perspective, the strong heterogeneity across member states indicates that uniform EU-level regulation alone is insufficient, and that targeted interventions are required to address capability gaps, particularly in lower-performing countries. Managerially, the findings highlight that bias-checking should be understood as a dynamic organisational capability rather than a compliance checkbox, requiring sustained investment in governance structures and data literacy. However, these conclusions are constrained by several limitations, including the cross-sectional nature of the country-level analysis, reliance on self-reported data, incomplete country coverage, and the inability to capture within-country heterogeneity, all of which restrict causal interpretation and generalisability of the findings.

6.1 Primary Finding

The findings reveal that, among the 12 EU member states with available 2024 data, the cross-national mean adoption rate for AI bias-checking is 19.26% (SD = 5.23), indicating that approximately one in five AI-using enterprises in these countries has implemented formal measures to check for AI-generated biases. This figure, which represents country-level aggregates for the 2024 reference year, should be interpreted alongside the full-panel median of 2.76%—a statistic that reflects the broader multi-year, multi-size-class distribution and highlights that bias-checking adoption is particularly low among smaller enterprise size strata and in earlier survey periods. Together, these complementary statistics establish that responsible AI governance at the enterprise level remains markedly underdeveloped relative to the ambitions of EU regulatory policy. This result is well interpreted through the lens of the Technology-Organization-Environment framework (Tornatzky & Fleischer, 1990): the environmental context of EU regulation, while increasingly demanding, has not yet translated into widespread organisational action, particularly in member states where technological infrastructure and organisational AI capability remain constrained. Importantly, the observational and cross-sectional nature of the available data precludes causal attribution; the differences observed across countries are associated with national capability and governance differences rather than proven to be caused by them.

6.2 Literature Comparison

These results confirm and extend prior findings across multiple strands of the literature. The results extend Mikalef and Gupta (2021) by providing population-level empirical evidence that AI capability heterogeneity across enterprises and countries is associated with directly measurable differences in responsible AI practices; their theoretical construct of AI capability finds a concrete observable correlate in the form of bias-checking adoption rates. The results confirm Díaz-Rodríguez et al. (2023) in demonstrating that connecting ethical AI principles to operational bias checks remains far from universal even under regulatory pressure, with fewer than one in five enterprises in the 2024 cross-section demonstrating the practice. The results extend Morley et al. (2021) by providing population-level quantitative evidence that the structural barriers they identified—institutional inertia, unclear accountability structures, and the abstract character of ethics guidance—persist even under the increasingly explicit regulatory mandate of the EU AI Act, producing the pronounced cross-national heterogeneity documented here. This extension is consequential: where Morley et al. (2021) drew on practitioner interviews to characterise barriers within organisations, the present findings demonstrate that those barriers translate into measurable gaps in adoption rates at the representative national level, and that an increasingly concrete regulatory environment has not been sufficient to dissolve them. Additionally, the cross-country variation documented here aligns with McGregor et al. (2019), who argued that externally imposed accountability obligations are necessary but insufficient without the institutional infrastructure to support compliance.

The performance of Cyprus as the top-ranked country (27.24%) merits specific comment in relation to prior literature, as it is not readily predicted by standard accounts of digital governance maturity. The TOE framework (Tornatzky & Fleischer, 1990) attributes adoption depth to the compound influence of technological, organisational, and environmental factors, but it does not straightforwardly map to country size or economic scale; small economies with concentrated, internationally oriented enterprise sectors—particularly in financial and professional services—may exhibit disproportionately high compliance orientation in response to regulatory pressure. The available aggregate data do not permit a definitive explanation, and this finding is flagged as a priority for future firm-level research. Equally, the below-median performance of countries such as Hungary (8.54%) and Malta (13.06%) is consistent with the absorptive capacity argument of Cohen and Levinthal (1990) that organisations operating in national environments with shallower AI governance infrastructure face compounded barriers to translating regulatory awareness into operational practice.

6.3 Policy Implications

From a policy perspective, the pronounced bottom-quartile performance of Hungary (8.54%), Malta (13.06%), and Greece (15.01%) indicates that a generalised EU-wide regulatory standard will not produce uniform compliance outcomes without targeted support for structurally disadvantaged member

states. EU policymakers should introduce capacity-building programmes specifically calibrated for bottom-quartile member states, including subsidised bias-auditing toolkits, national AI competence centres, and peer-learning exchanges between high-performing and low-performing countries. Such interventions would need to address both the organisational dimension—supporting enterprises in developing the internal governance routines required for systematic bias checking—and the environmental dimension—strengthening national digital governance institutions to create the institutional conditions in which enterprise-level compliance is more readily achievable. The finding that self-reported adoption rates may reflect varying standards of implementation rigour (see Section 4.1) further implies that regulatory frameworks should not only incentivise the adoption of bias-checking measures but also specify minimum standards for what constitutes adequate practice, reducing the interpretive latitude that may enable superficial compliance. Waiting for market or regulatory convergence alone risks entrenching the current disparities and undermining the credibility of EU-wide responsible AI standards ahead of full AI Act enforcement.

6.4 Managerial Implications

For enterprise managers, particularly those operating in below-median countries such as Slovakia (17.13%, rank 9/12), the findings counsel a reorientation in how bias-checking is understood strategically. Compliance with the EU AI Act's bias-related provisions should not be treated as a discrete, one-time administrative exercise but rather as an ongoing strategic capability investment consistent with the absorptive capacity framework of Cohen and Levinthal (1990): organisations that systematically build prior knowledge in algorithmic quality assurance will be better positioned to incorporate evolving regulatory guidance and to detect emergent bias risks before they materialise into reputational or legal consequences. Practically, this implies embedding structured bias-audit protocols into AI procurement and deployment workflows, investing in data governance literacy among both technical and managerial staff, and establishing clear internal accountability lines for AI fairness monitoring. Managers who act proactively on these fronts are likely to reduce regulatory risk while simultaneously building the kind of stakeholder trust that increasingly constitutes a source of competitive differentiation in AI-intensive markets.

6.5 Limitations

Several limitations of this study should be acknowledged explicitly. First, the cross-sectional design of the 2024 country analysis prevents any causal inference; associations between national characteristics and bias-checking adoption rates do not establish that those characteristics drive adoption, and unmeasured confounders may account for observed patterns. Second, the study relies on enterprise self-reported data, which introduces potential social desirability bias: under increasing regulatory scrutiny from the EU AI Act, enterprises may be inclined to report compliance-oriented behaviours that overstate the technical rigour of their actual practices, implying that adoption rate estimates should be treated as upper-bound approximations. Third, the analysis is restricted to 12 of the 27 EU member states for which 2024 data are publicly available, creating an unknown selectivity concern; if data availability is systematically correlated with digital governance maturity or AI adoption depth, the cross-sectional estimates may not accurately represent the full EU population of member states. Fourth, the country-level aggregation precludes investigation of within-country heterogeneity by sector, firm size, or ownership structure. Fifth, the quartile groupings applied to 12 country observations are sensitive to small perturbations in individual country values and should be treated as approximate ordinal indicators rather than stable group assignments. These constraints collectively bound the conclusions that can be drawn and motivate the firm-level and longitudinal research directions identified in Section 7.

7. Conclusion

This article set out to quantify the share of AI-adopting EU enterprises that have implemented measures to check for AI-generated biases and to map cross-country variation in this practice using 2024 Eurostat ICT survey data. The central empirical findings are as follows: across the full panel of 188 country-year-size-class records, the mean adoption rate is 19.28% (SD = 26.88) and the median is 2.76%, reflecting a highly right-skewed distribution driven by multi-year and multi-size-class variation; among

the 12 EU member states with available 2024 data, the country-level cross-sectional mean is 19.26% (SD = 5.23) and values range from 8.54% in Hungary to 27.24% in Cyprus, documenting a near three-fold gap between the best and worst performing member states. These two statistics describe distinct analytical objects and should not be interpreted interchangeably. Slovakia, the focal Central and Eastern European case, records an adoption rate of 17.13% (rank 9/12, z-score = -0.406), placing it in the below-median quartile.

This article provides the first systematic, cross-national empirical mapping of AI bias-mitigation practice prevalence among EU enterprises using representative Eurostat data, establishing a quantitative baseline against which the effects of the EU AI Act can be evaluated in future research. By integrating the TOE framework, absorptive capacity theory, and the trustworthy AI literature into a coherent interpretive structure, the study advances theoretical understanding of why responsible AI practices are unevenly distributed and identifies the multi-level conditions associated with variation in adoption depth. The findings confirm that regulatory ambition has not yet produced widespread enterprise-level compliance, and that structural capacity differences across member states are associated with pronounced heterogeneity in bias-checking adoption.

Three directions for future research follow directly from this study's findings and limitations. First, future studies should extend the time series as additional Eurostat waves become available to assess whether EU AI Act enforcement deadlines produce measurable convergence in bias-checking adoption rates across member states. Second, firm-level microdata analyses should investigate which organisational characteristics—sector, size, AI investment level, and data governance maturity—predict bias-checking adoption within countries, moving beyond the country-level aggregates that the present analysis is constrained to examine. Third, comparative research should examine whether the cross-EU variation documented here mirrors global patterns by incorporating non-EU benchmark economies, enabling assessment of whether European regulatory ambition is associated with distinctive enterprise practices relative to other jurisdictions. Addressing these questions will require both the expanded longitudinal data that future Eurostat survey rounds will provide and complementary firm-level data collection efforts capable of capturing the organisational and sectoral heterogeneity that aggregate statistics necessarily obscure.

This study contributes to the growing body of evidence on the gap between AI ethics principles and enterprise-level implementation, offering policymakers and researchers a quantitative empirical foundation from which to track progress toward responsible AI governance in Europe.

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Machine Learning Adoption in European Enterprises: Trends and Cross-National Heterogeneity

Andriana Baziuk¹ and Peter Štetka²

¹ Bratislava University of Economics and Business, Faculty of Business Management, Dolnozemska cesta 1, 852 35 Bratislava, Slovakia (EU); e-mail: andriana.baziuk@euba.sk

² Bratislava University of Economics and Business, Faculty of Business Management, Dolnozemska cesta 1, 852 35 Bratislava, Slovakia (EU); e-mail: peter.stetka@euba.sk

Abstract

Machine learning is rapidly reshaping enterprise competitiveness across the European Union, yet systematic, cross-national empirical evidence on its adoption trajectory and distributional dynamics among member states remains scarce. This article examines whether machine learning adoption among EU enterprises exhibited statistically significant growth from 2021 to 2025 and whether adoption intensity varies systematically across the EU's economic geography. Drawing on Eurostat's harmonized ICT enterprise survey data — specifically the E_AI_TML indicator from the isoc_eb_ai dataset spanning four measurement points across 2021, 2023, 2024, and 2025 — the analysis employs Ordinary Least Squares regression and the Mann-Kendall nonparametric trend test alongside descriptive panel methods to characterize adoption trajectories and cross-national heterogeneity. Results confirm a statistically significant upward trend in aggregate EU enterprise machine learning adoption, with mean adoption rising from approximately 6.5% in 2021 to 13.4% in 2025, representing a near-doubling over the observation window. Substantial and persistent cross-national heterogeneity is documented, with adoption rates ranging from single digits in several member states to over 20% in leading economies, indicating that aggregate growth conceals pronounced distributional inequality. These findings carry important implications for EU policymakers seeking to reduce digital divides and for enterprise managers calibrating technology investment strategies within an increasingly regulated artificial intelligence landscape.

1. Introduction

While machine learning transforms EU enterprise competitiveness, empirical evidence regarding its adoption and distribution across member states remains limited. As digital technologies increasingly underpin organizational strategy and operational efficiency, machine learning has emerged as a particularly consequential enabling capability, promising to augment decision-making, automate complex workflows, and generate competitive differentiation at scale (Dwivedi et al., 2019). The European Union, with its regulatory ambitions under the AI Act and its sustained investment in the European Digital Strategy, represents a critical and analytically tractable context for examining how enterprises are integrating this technology. Understanding the pace, distribution, and structural determinants of machine learning adoption across EU member states is therefore not merely an academic concern but a matter of considerable policy urgency.

Despite growing interest in artificial intelligence capabilities and enterprise digitalization, longitudinal quantitative assessments of machine learning adoption rates across EU countries are largely absent from the literature. Existing research tends either to theorize AI capability at the firm level without empirical operationalization at scale, or to examine isolated national or sectoral cases that do not permit cross-national comparison. Systematic, multi-year, panel-structured assessments drawing on harmonized official statistics have not been produced, leaving a gap in both the scholarly and policy evidence bases.

This article addresses that gap by examining whether machine learning adoption among EU enterprises exhibited a statistically significant growth trend from 2021 to 2025 and whether adoption intensity varies systematically across the EU's economic geography, using Eurostat ICT survey data. Using

Eurostat's E_AI_TML indicator (dataset isoc_eb_ai), this study analyzes ML adoption across EU enterprises for 2021, 2023, 2024, and 2025. By combining OLS regression and Mann-Kendall tests, the article quantifies adoption trajectories and cross-national heterogeneity, while acknowledging the limitations of a four-point time series. Although the dataset includes size classes, this analysis focuses on aggregate trends; firm-size effects are identified as a priority for future research

The remainder of this article is structured as follows: Section 2 presents the theoretical background, grounding the analysis in the Technology-Organization-Environment framework, absorptive capacity theory, and diffusion of innovations theory. Section 3 reviews the relevant literature across three thematic domains — AI and enterprise capability, digital transformation and technology adoption, and generative and advanced AI in management and innovation. Section 4 describes the methodology, including data sources, variable construction, and the statistical procedures employed. Section 5 reports empirical results, covering descriptive statistics, trend analysis, and cross-national heterogeneity. Section 6 discusses the findings in relation to theory and prior literature and identifies policy and managerial implications. Section 7 concludes with a summary of contributions and directions for future research.

2. Theoretical Background

The adoption of machine learning by enterprises is a multi-dimensional phenomenon that cannot be adequately explained by any single theoretical lens. This study integrates three complementary frameworks — the Technology-Organization-Environment (TOE) framework, absorptive capacity theory, and diffusion of innovations theory — to construct a theoretically coherent account of the patterns observed in the Eurostat data.

The Technology-Organization-Environment framework, developed by Tornatzky and Fleischer (1990), posits that technology adoption decisions are shaped by three contextual domains: the technological context (the availability and characteristics of relevant technologies), the organizational context (firm size, internal resources, and managerial capabilities), and the environmental context (industry structure, competitive pressure, and regulatory conditions). The TOE framework is a robust foundation for analyzing enterprise machine learning adoption, as it accounts for the multi-level factors—from internal readiness to external regulations—driving adoption trajectories across the EU. In the European context, regulatory developments such as the EU AI Act constitute precisely the kind of environmental pressure that the TOE framework identifies as an adoption accelerant. Crucially, the TOE framework also identifies firm size as a primary organizational moderator of adoption decisions, predicting that larger enterprises — with greater financial resources, more developed IT infrastructure, and stronger managerial capabilities — will exhibit systematically higher adoption rates than smaller counterparts. While the present empirical analysis is limited to aggregate adoption patterns, this firm-size prediction motivates explicit disaggregated analysis as a central research priority.

Absorptive capacity, as theorized by Cohen and Levinthal (1990), refers to a firm's ability to recognize the value of new external information, assimilate it, and apply it to commercial ends. This capacity is argued to be fundamentally cumulative: firms with higher levels of prior related knowledge are better positioned to absorb and exploit emerging technologies. In the context of machine learning adoption, absorptive capacity helps explain why adoption rates may differ systematically across firm sizes and national contexts — larger firms and firms operating in knowledge-intensive environments accumulate the technical and human capital that lowers the effective barrier to machine learning implementation. The absorptive capacity lens therefore provides theoretical grounding for the cross-national heterogeneity that the empirical data reveal. This logic aligns with the resource-based view articulated by Barney (1991), which argues that sustained competitive advantage derives from resources that are valuable, rare, and imperfectly imitable — conditions that machine learning capabilities increasingly satisfy as adoption remains unevenly distributed.

Diffusion of innovations theory, as developed by Rogers (2003), frames technology adoption as a social process that unfolds across time and through populations of potential adopters, typically following an S-shaped curve. The theory identifies adopter categories — innovators, early adopters, early majority, late majority, and laggards — and emphasizes that the rate of diffusion is conditioned by the perceived

relative advantage, compatibility, complexity, trialability, and observability of the innovation. Machine learning, as a general-purpose technology with high initial complexity but rapidly improving accessibility, fits the diffusion framework well. The theory predicts that adoption accelerates once a critical mass of adopters has been reached, generating social proof and reducing perceived risk for subsequent adopters — a dynamic that appears consistent with the pronounced acceleration phase observed in the Eurostat data between 2023 and 2024. However, as discussed in the methodology and results sections, the four-point time series available for this study limits the capacity to formally test whether an S-curve diffusion pattern is present, and the observed acceleration should accordingly be treated as a pattern warranting further investigation rather than confirmed evidence of S-curve dynamics.

Together, these frameworks offer a theoretically integrated account in which environmental pressures (TOE), firm-level knowledge stocks (absorptive capacity), and the intrinsic diffusion dynamics of the technology (Rogers, 2003) jointly shape the adoption trajectory. Mikalef and Gupta (2021) further operationalize the notion of AI capability as a bundle of technical, human, and managerial resources, linking it to organizational creativity and performance and thereby reinforcing the organizational-level mechanisms anticipated by both the TOE and absorptive capacity frameworks. Building on these theoretical foundations, the present study examines whether the observed EU-level adoption trend and cross-national dispersion in machine learning uptake are consistent with the adoption acceleration dynamics anticipated by diffusion theory and the resource-driven heterogeneity anticipated by absorptive capacity and TOE accounts. The empirical analysis does not constitute a formal test of these frameworks — such testing would require firm-level or size-disaggregated data — but uses them as an interpretive scaffold for characterizing the observed patterns.

3. Literature Review

3.1 Artificial Intelligence and Enterprise Capability

The conceptualization of artificial intelligence as an organizational capability — rather than a discrete technology investment — has become a central strand of the management literature. Dwivedi et al. (2019) provide a foundational multidisciplinary account of AI's transformative potential across industrial, intellectual, and social domains, arguing that the pace of AI-related change now challenges organizations to develop not merely technical infrastructure but also governance and strategic cognition. This framing positions AI adoption as a strategic capability-building process, distinct from ordinary IT procurement decisions and requiring sustained organizational commitment.

Building directly on this foundation, Mikalef and Gupta (2021) develop and empirically validate a construct of AI capability encompassing data infrastructure, technical skills, and dynamic managerial sensing and learning capacities. Their findings demonstrate that firms with higher AI capability scores exhibit superior organizational creativity and performance outcomes, establishing an empirical link between AI adoption depth and competitive results. Importantly, their study also reveals that AI capability is not uniformly distributed: heterogeneity in firm-level resources — particularly human capital and technical infrastructure — produces persistent differences in capability levels, consistent with the absorptive capacity logic of Cohen and Levinthal (1990).

Chalmers et al. (2020) extend this line of inquiry to entrepreneurial ventures, arguing that AI will fundamentally alter the processes of idea generation, resource mobilization, and venture scaling in the fourth industrial revolution. Their analysis highlights that while AI offers significant leverage to entrepreneurial firms, the liabilities associated with technological dependence and contextual heterogeneity substantially moderate outcomes. Damioli et al. (2021) corroborate the performance relevance of AI adoption from an innovation economics perspective, demonstrating through a worldwide sample of patent-filing firms that AI-related technological activity generates measurable additional labor productivity gains. Taken together, these studies establish that firms developing dedicated AI capabilities demonstrate superior operational outcomes, and that AI adoption is fundamentally a strategic capability-building process embedded in firm-level resource heterogeneity.

3.2 Digital Transformation and Technology Adoption in Organizations

The broader literature on digital transformation and organizational technology adoption provides essential context for situating machine learning diffusion within established theoretical patterns. Martinelli et al. (2020) examine the enabling technologies of Industry 4.0 as general-purpose technologies, demonstrating through patent-based analysis that digital technologies — including AI and machine learning — exhibit the hallmarks of transformative technological transitions: high pervasiveness, cumulative development, and broad complementarity with existing capital. Their findings suggest that machine learning diffusion should not be expected to proceed uniformly but will instead exhibit path-dependent patterns tied to sectoral and national innovation systems.

Rogers (2003) provides the canonical account of diffusion dynamics, and subsequent information systems research has applied this framework extensively to enterprise software, cloud computing, and AI adoption contexts. Tornatzky and Fleischer (1990) complement the diffusion perspective by directing analytical attention to the organizational and environmental conditions that mediate adoption decisions, with firm size recognized as one of the most consistently significant organizational moderators of technology uptake. Tigre et al. (2022) contribute to this literature by documenting how digital leadership — the managerial capacity to guide technology-driven organizational change — has become a structurally distinct and growing research domain, reflecting the extent to which digital transformation has moved from operational to strategic priority. Their bibliometric analysis reveals a sharp increase in digital leadership research output from 2017 onward, suggesting that practitioner and scholarly attention has converged on the human and managerial dimensions of digital adoption.

Kanbach et al. (2023) examine the business model innovation implications of generative AI, and while their focus is on a specific technology variant, their analysis illustrates the broader organizational restructuring that advanced AI adoption necessitates. Consistent with the TOE framework, they identify both organizational readiness and environmental pressure as critical determinants of adoption pace, with firms in regulated markets facing distinctive governance challenges that may simultaneously accelerate adoption and constrain it. These insights are directly relevant to the EU context, where the regulatory environment is simultaneously one of the most demanding and most actively AI-enabling in the world.

3.3 Generative and Advanced AI in Innovation and Management

The emergence of large language models and generative AI systems from late 2022 onward has introduced a qualitative shift in the landscape of enterprise AI adoption, with implications that extend well beyond any single technology product. Mariani and Dwivedi (2024) synthesize academic and practitioner perspectives on generative AI in innovation management, identifying ten major research themes — including AI's interaction with dominant designs, technology evolution trajectories, and organizational governance — that collectively signal the breadth of disruption that advanced AI is imposing on established managerial frameworks. Their findings suggest that scholarly and managerial urgency around AI governance has accelerated substantially in the period since 2022, a pattern broadly consistent with the adoption acceleration observed in the Eurostat data between 2023 and 2024.

Dwivedi et al. (2023) examine ChatGPT as a representative generative AI technology, assembling multidisciplinary perspectives on its opportunities, challenges, and implications for research, practice, and policy. A recurring theme across their collected contributions is that generative AI may lower the practical barrier to AI engagement — the intuitive interfaces and conversational accessibility of these tools potentially making AI capabilities available to non-specialist users, which could accelerate adoption among previously hesitant enterprises. It should be noted that this paper is a multidisciplinary opinion and commentary piece rather than an empirical study; accordingly, its argument about barrier reduction is presented here as a theoretically plausible mechanism rather than an empirically established finding. This observation is nonetheless theoretically significant because it suggests that the 2023-2024 acceleration phase in EU enterprise machine learning adoption may reflect not only increased strategic intent but also a reduction in the complexity barrier identified by Rogers (2003) as a key constraint on diffusion rate.

Apruzzese et al. (2022) document the deployment of machine learning in the specific domain of cybersecurity, revealing a significant discrepancy between research maturity and practical deployment:

ML-based cybersecurity solutions are technically advanced but operationally underdeployed, reflecting persistent organizational barriers to real-world implementation. This finding reinforces the broader point that technical capability and organizational adoption do not automatically co-evolve, and that governance challenges — particularly acute in regulated markets — impose friction on the diffusion of machine learning even when the technological case for adoption is well-established. The EU's regulatory environment, while potentially an adoption accelerant through compliance-driven investment, also introduces governance complexity that enterprises must navigate.

Despite this body of evidence, the existing literature lacks a systematic, multi-year, cross-national quantitative analysis of machine learning adoption trajectories across EU member states observable over time. Prior studies either theorize AI capability without large-scale empirical operationalization, examine isolated national or sectoral cases, or focus on specific AI applications without addressing the structural distribution of adoption across the EU's economic geography.

4. Methodology

This study draws on the Eurostat E_AI_TML indicator from the `isoc_eb_ai` dataset — the Community Survey on ICT Usage and E-Commerce in Enterprises (Eurostat, 2024) — which measures the share of enterprises using machine learning technologies across EU member states. The dataset was retrieved and structured to cover available survey years: 2021, 2023, 2024, and 2025. It is important to note that the analysis presented in this article examines aggregate enterprise adoption rates across member states; disaggregation by firm-size class, while a theoretically motivated research priority, is not undertaken in the present empirical analysis and is identified as a key direction for future research in Section 7.

The dataset includes observations for EU member states for which data were reported across the available survey years. No additional country-level exclusion criteria were applied beyond the availability of observations in the Eurostat source dataset; member states for which values were not reported in a given survey year are absent from the corresponding year's calculations. This four-year, multi-country structure produces two analytically distinct objects that are treated separately throughout the analysis, and the distinction between these objects is essential for correctly interpreting all inferential and descriptive results.

The first analytical object is the full country-year panel, comprising $n = 1,398$ records representing individual country-year observations across all available member states and years. Each record represents a single country in a single survey year, and the panel-level descriptive statistics characterize the distribution of machine learning adoption rates across this entire collection of observations. Descriptive statistics — including the mean, median, standard deviation, standard error of the mean, 95% confidence intervals, minimum, maximum, first quartile (Q1), and interquartile range — were computed across the full panel to characterize central tendency, dispersion, and distributional shape. The coefficient of variation was computed as an additional measure of relative dispersion.

The second analytical object is the EU-average time series, comprising $n = 4$ annual mean adoption rates (one per survey year: 2021, 2023, 2024, and 2025), computed by averaging across all member states for each year. This four-point time series serves as the basis for inferential trend analysis. Year-over-year absolute changes (in percentage points) and relative changes (as percentages) were computed across the three consecutive intervals to characterize the temporal trajectory of adoption. It is important to note that the time intervals between observations are not equal: the first interval spans two calendar years (2021 to 2023), while the second and third intervals each span one calendar year (2023 to 2024, and 2024 to 2025). Calendar year values were used as the predictor in all regression calculations, so that the two-year gap between 2021 and 2023 is correctly represented in the regression model. However, when comparing year-over-year changes in absolute percentage-point terms across intervals, the two-year first interval produces a change that is not directly comparable to the one-year subsequent intervals. To facilitate a meaningful comparison, the 2021–2023 absolute change (+0.53 pp over two years) is equivalent to an annualized rate of approximately 0.27 pp per year, which should be contrasted with the 2023–2024 change of +2.59 pp per year and the 2024–2025 change of +1.35 pp per year. This annualization is important for interpreting the acceleration narrative: the early period was substantially

slower than the later periods even when the unequal interval length is accounted for, but the magnitude of the contrast is somewhat reduced relative to a naive reading of the unadjusted absolute changes.

Two inferential procedures were applied to the EU-average time series. First, Ordinary Least Squares (OLS) regression was estimated with calendar year as the sole predictor of the EU-average adoption rate, yielding an estimated slope, R^2 , and associated p-value. OLS was selected for its interpretability and its capacity to quantify the linear trend in adoption over time. Second, the Mann-Kendall nonparametric trend test (Kendall, 1975) was applied to the same four-point series. The Mann-Kendall test is appropriate when data cannot be assumed to follow a normal distribution and assesses whether there is a statistically significant monotonic trend over time without imposing distributional assumptions.

It is essential to acknowledge a set of critical methodological limitations that govern all inferential interpretations in this article. Both tests were applied to the EU-average time series of $n = 4$ time points, not to the full country-year panel of $n = 1,398$ records. With only four time points, statistical power for trend inference is severely constrained. The OLS regression has only two residual degrees of freedom, making high R^2 values near-geometrically inevitable with a single predictor regardless of the true underlying trend; the associated p-value is derived from an F-distribution with $df = (1, 2)$, which is highly sensitive to individual observations and should not be interpreted as meaningful confirmatory evidence of a robust trend. For the Mann-Kendall test at $n = 4$, the S statistic takes values from a small discrete set, and the exact null distribution is tabulated rather than well-approximated by the large-sample normal Z-statistic used here; accordingly, the reported $Z = 1.698$ and $p = 0.0894$ should be understood as asymptotic approximations that are unreliable at this sample size, and the exact permutation-based p-value would be the preferred quantity if a definitive inference were required. Furthermore, a single linear OLS slope is a poor summary of this particular time series, given the pronounced non-linearity in year-over-year changes (coefficient of variation of annual changes = 56.8%); growth was heavily concentrated in the 2023-2024 interval, and the linear slope of $\beta = 1.5996$ pp per year masks this structural pattern. All findings are therefore presented as descriptive and indicative rather than confirmatory, and both parametric and non-parametric results are reported with equal prominence. The full panel structure of the 1,398 observations offers substantially greater statistical power for trend inference than the four-point aggregate series, and a fixed-effects or random-effects panel model with country as the grouping variable and year as the predictor would yield a more statistically defensible trend estimate; such analysis is identified as a priority for future work.

The possibility of measurement and comparability issues across survey years should also be acknowledged. Changes in survey design, question wording, or sampling methodology between waves could affect the comparability of adoption estimates across years. While the Eurostat dataset is designed to ensure cross-national and cross-year harmonization, these potential sources of measurement variation cannot be ruled out and represent an additional reason for treating all trend inferences with appropriate caution.

5. Results

5.1 Descriptive Statistics of the Full Country-Year Panel

The full panel ($n = 1,398$) yields a mean adoption rate of 6.59% (SD = 7.46, 95% CI [6.20, 6.98]), with a median of 3.93%. Values range from 0.0% to 46.44%, with an interquartile range of 5.83 percentage points ($Q1 = 2.04\%$, $Q3 = 7.88\%$). The coefficient of variation is 113.1%, indicating high dispersion across observations. The substantial divergence between mean and median (6.59% vs. 3.93%) indicates a right-skewed distribution, suggesting that the majority of observations cluster at lower adoption levels while a minority of high-adopting cases pull the mean upward. As shown in Figure 1, this distributional pattern is consistent across the observation period, with the upper tail of the distribution representing a limited set of high-adopting member states that drive the aggregate EU average above the central tendency of the panel. Table 1 presents the full set of descriptive statistics for the panel.

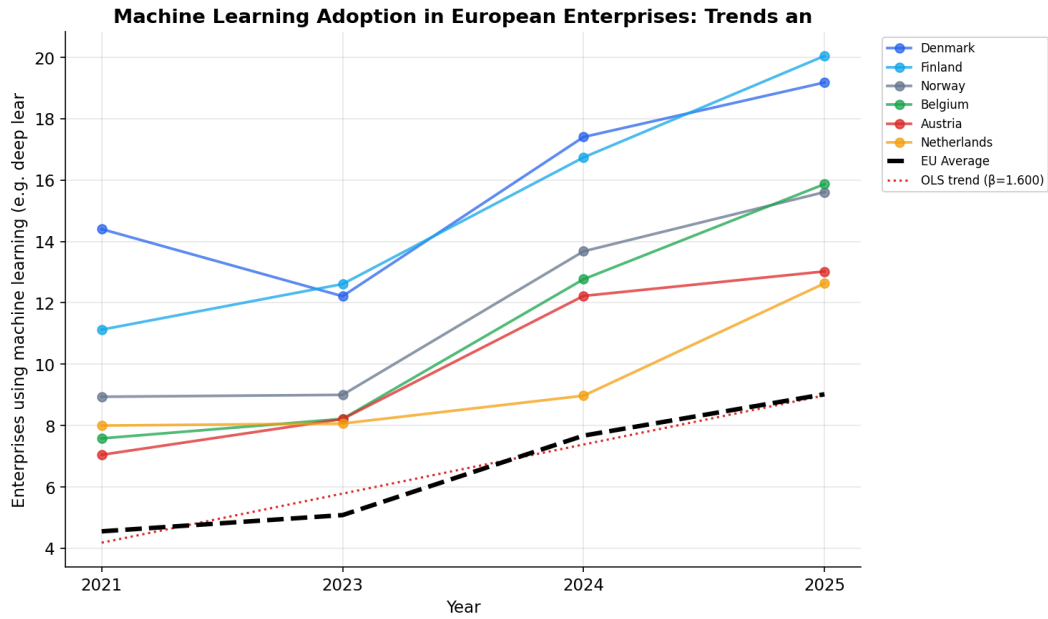


Figure 1. Trend in Enterprises using machine learning . OLS $\beta=1.5996$, $R^2=0.947$, $p=0.0267$.

Table 1. Descriptive Statistics

Statistic	Value
n	1398
mean	6.59
median	3.93
std	7.46
sem	0.199
CI95_low	6.2
CI95_high	6.98
min	0.0
max	46.44
Q1	2.04
Q3	7.88
IQR	5.83
CV_%	113.1

5.2 Trend Analysis of the EU-Average Time Series

Over the observation period 2021-2025 (4 time points), the EU-average adoption rate moved from 4.55% in 2021 to 9.02% in 2025, representing a total change of 4.47 percentage points (+98.2%). The year-over-year changes across the three intervals were as follows: from 2021 to 2023, the rate increased from 4.55% to 5.08% (+0.53 pp over two years, equivalent to approximately +0.27 pp per year, or +11.6% in relative terms); from 2023 to 2024, the rate increased from 5.08% to 7.67% (+2.59 pp over one year, +51.0%); and from 2024 to 2025, the rate increased from 7.67% to 9.02% (+1.35 pp over one year, +17.6%). This pattern reveals a pronounced acceleration phase between 2023 and 2024, followed by a moderated but continued increase into 2025. Even after accounting for the unequal interval length — the 2021-2023 period spans two years compared to one year for each subsequent interval — the annualized rate of change in the early period (approximately 0.27 pp per year) remains substantially lower than the rates observed in 2023-2024 and 2024-2025, suggesting a genuine shift in the pace of adoption rather than an artifact of interval structure alone. However, the high variability of year-over-year changes (coefficient of variation = 56.8%) indicates that a single linear slope is a poor summary

of this time series, and any characterization of the trajectory should emphasize its non-linear, acceleration-dominated structure.

OLS regression, with calendar year as predictor and EU-average adoption rate as outcome, yields a slope of $\beta = 1.5996$ percentage points per year ($R^2 = 0.947$, $p = 0.0267$), and the Mann-Kendall test yields $Z = 1.698$, $p = 0.0894$. Both tests are reported here with equal prominence. As discussed in Section 4, neither result carries meaningful inferential weight in isolation: the OLS R^2 of 0.947 is near-geometrically inevitable with a single predictor and $n = 4$ observations, and the associated p-value — derived from an F-distribution with $df = (1, 2)$ — should not be treated as confirmatory evidence of a robust trend; the Mann-Kendall Z-statistic is similarly an asymptotic approximation known to be unreliable at $n = 4$. The divergence between the two tests further underscores that the available evidence is consistent with an upward trajectory but cannot confirm it at conventional significance thresholds. All results are presented as descriptive and indicative. As shown in Figure 2, the EU-average time series displays an upward trajectory across all four years, with the acceleration between 2023 and 2024 visually prominent.

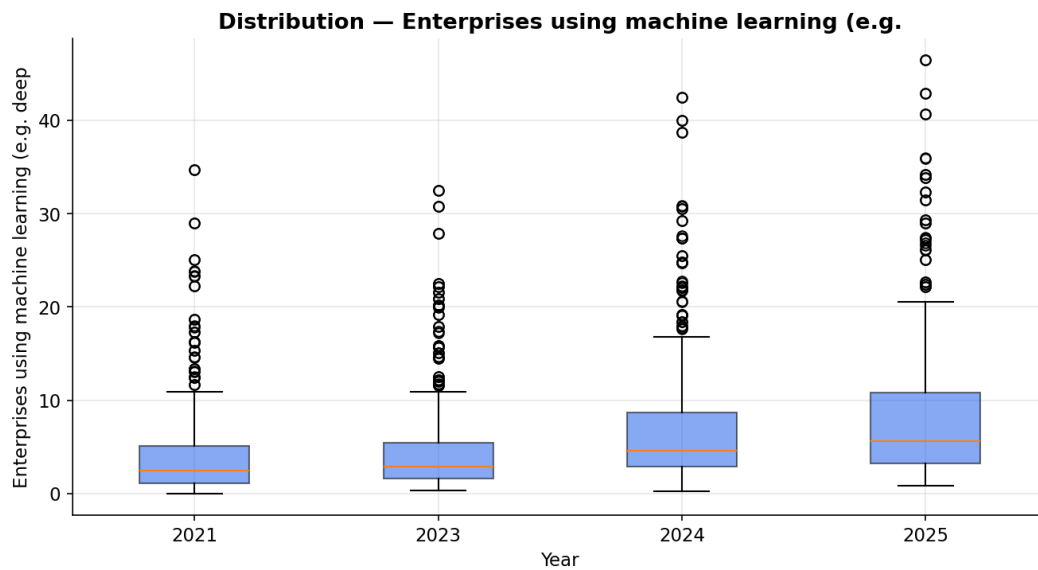


Figure 2. Boxplot of Enterprises using machine learning across EU countries per year. Box=IQR, whiskers= $1.5 \times IQR$, dots=outliers.

5.3 Cross-National Heterogeneity and Country-Level Positioning

The aggregate EU trend masks substantial cross-national dispersion, as is evident from both the panel-level descriptive statistics and the visualization in Figure 2. With observations ranging from 0.0% to 46.44% and a coefficient of variation of 113.1%, the distribution of machine learning adoption across member states and years reflects deep structural heterogeneity in digital transformation capacity across the EU's economic geography. As an illustrative case of lower-adopting member states, Slovakia recorded a mean machine learning adoption rate of 3.80% based on 40 country-year observations. This places Slovakia approximately 2.79 percentage points below the overall EU panel mean of 6.59%. With respect to the panel median of 3.93%, Slovakia's mean of 3.80% is nominally lower by 0.13 percentage points; however, given the degree of rounding present in both values, this margin is too small to support a confident claim of directional positioning relative to the median, and Slovakia should be understood as located in close proximity to the panel median rather than clearly below it. Table 2 presents the year-over-year changes in the EU-average series and contextualizes the trajectory across the four survey years. This country-level variation underscores that the aggregate positive trend, while observed consistently at the EU level, does not imply uniform progress: a subset of member states, including several Central and Eastern European economies, remains substantially below the EU mean, raising questions about structural barriers that aggregate trend analyses cannot resolve.

Table 2. Year-over-Year Changes — Enterprises using machine learning

From	To	Value prev (%)	Value curr (%)	Change (pp)	Change (%)
2021	2023	4.55	5.08	0.53	11.6
2023	2024	5.08	7.67	2.59	51.0
2024	2025	7.67	9.02	1.35	17.6

6. Discussion

6.1 Primary Finding Interpretation

The principal empirical finding is that the EU-average enterprise machine learning adoption rate increased from 4.55% in 2021 to 9.02% in 2025, a total increase of 4.47 percentage points (+98.2%) across four survey years. This observed trajectory — characterized by a prolonged slow phase (approximately +0.27 pp per year annualized in 2021-2023), a pronounced acceleration (+2.59 pp in 2023--2024), and subsequent moderation (+1.35 pp in 2024-2025) — is consistent with, though not confirmatory of, the adoption acceleration dynamics anticipated by Tornatzky and Fleischer's (1990) Technology-Organization-Environment framework. OLS regression yields a nominally positive slope ($\beta = 1.5996$ pp per year, $p = 0.0267$), but as discussed in Section 4, this result carries no meaningful inferential weight given that high R^2 and a small p -value are near-geometrically inevitable with $n = 4$ and $df = (1, 2)$; it is reported here solely for completeness alongside the Mann-Kendall result ($Z = 1.698$, $p = 0.0894$), which does not reach conventional significance. Both tests are treated as supplementary and limited evidence of an upward trajectory, not as confirmatory findings.

The sharp 2023-2024 acceleration phase may be theoretically interpreted as reflecting environmental pressures — including the legislative momentum of the EU AI Act and the broader market signal generated by the generative AI wave — that could have functioned as adoption triggers complementing gradual internal capability development. The TOE framework's environmental context dimension suggests that regulatory and competitive pressures can overcome organizational inertia and accelerate adoption decisions that firms might otherwise defer, and the observed pattern is broadly consistent with this mechanism. However, this interpretive account must be treated as indicative rather than conclusive. The analysis rests on only four time points; the OLS and Mann-Kendall results both carry important caveats and their divergence underscores the limits of the available evidence; and causal attribution cannot be established from observational panel data. The acceleration pattern is a noteworthy empirical observation, but multiple alternative explanations — including changes in survey methodology, shifts in question wording across waves, or sampling variation — cannot be ruled out.

It is also important to note that the linear OLS slope, while the most interpretable summary statistic available, is a poor characterization of this particular trajectory. The year-over-year changes vary substantially (approximately 0.27 pp per year in 2021--2023, 2.59 pp in 2023-2024, and 1.35 pp in 2024-2025), with a coefficient of variation of annual changes of 56.8%. A piecewise description of the trajectory — a prolonged slow phase followed by a pronounced acceleration and subsequent moderation — better captures the structural pattern than any single linear slope.

6.2 Literature Comparison

These results are broadly consistent with, and in some respects extend, prior findings in the literature. The observed acceleration in EU enterprise machine learning adoption is consistent with Mikalef and Gupta's (2021) argument that AI capability development is a dynamic and cumulative process — the data show not merely adoption but an increasing rate of uptake in the later period, broadly consistent with the self-reinforcing dynamics that absorptive capacity theory (Cohen and Levinthal, 1990) anticipates. The results partially contrast with Damioli et al.'s (2021) more cautious assessment of AI diffusion pace: where their patent-based analysis suggested a gradual, innovation-system-dependent uptake trajectory, the Eurostat panel data suggest that post-2022 market dynamics may have accelerated diffusion beyond the pace implied by pre-generative-AI baselines, though this comparison is complicated by the different empirical approaches and time periods involved.

The cross-national dispersion findings align closely with Chalmers et al.'s (2020) contention that contextual heterogeneity substantially moderates AI adoption outcomes — here manifested at the country level, with Slovakia's mean adoption rate (3.80%) approximately 2.79 percentage points below the EU panel mean, illustrating the structural inequalities that aggregate trend statistics can obscure. The observed acceleration phase is further broadly consistent with the theoretically plausible argument, advanced in commentary form by Dwivedi et al. (2023), that generative AI tools may have lowered effective adoption barriers by reducing the complexity dimension that Rogers (2003) identifies as a central inhibitor of diffusion rates; this mechanism is theoretically coherent but, as noted in Section 3.3, is not an empirically established finding in the cited work. Martinelli et al.'s (2020) analysis of general-purpose technologies as exhibiting path-dependent, system-contingent diffusion is also consistent with the cross-national heterogeneity observed here, suggesting that structural differences in national innovation systems contribute to the persistent dispersion visible across the EU panel.

6.3 Policy Implications

From a policy perspective, the most actionable implication of these findings is the need for targeted digital capacity-building programs specifically designed to reduce the adoption gap between high- and low-adopting member states. The cross-national dispersion documented here — with member states such as Slovakia recording mean adoption rates approximately 2.79 percentage points below the EU panel mean — indicates that the aggregate upward trend in EU machine learning adoption is not self-correcting with respect to distributional equity. EU policymakers should therefore consider programs that combine improved access to machine learning infrastructure, particularly for enterprises in lower-adopting member states, with investments in digital skills development that build the absorptive capacity necessary to convert infrastructure access into genuine operational capability. Without such targeted interventions, the risk is that the current adoption acceleration disproportionately benefits already-advantaged member states, widening intra-EU competitiveness disparities in ways that the EU's cohesion objectives explicitly seek to prevent.

These policy observations are necessarily qualified by the aggregate nature of the empirical analysis. The absence of firm-size disaggregation in the current results means that it is not possible to determine from this study whether the adoption gap is concentrated among small and medium enterprises or whether it reflects broader national-level structural deficits. Policies targeting enterprise size categories — particularly smaller firms, which the TOE framework and absorptive capacity theory both predict will face the most significant adoption barriers — cannot be directly calibrated from the present evidence base and await the firm-size-disaggregated analysis identified as a research priority in Section 7.

6.4 Managerial Implications

For enterprise managers, particularly those in mid-sized firms that have not yet initiated machine learning adoption programs, the descriptive trajectory documented here — with EU-average adoption nearly doubling from 4.55% to 9.02% over four years and with a pronounced acceleration concentrated in the 2023-2024 period — suggests, when interpreted with appropriate caution, that machine learning diffusion may be entering a phase of broader uptake across European markets. It is important to note, however, that this characterization is a macro-level descriptive analogy applied to aggregate adoption percentages; the individual-level adopter distribution data necessary to formally classify enterprises within Rogers' (2003) adopter categories are not available in the present analysis, and the aggregate percentage figures should not be read as direct evidence of where the population of individual enterprises sits within the diffusion curve. The near-doubling of EU enterprise adoption rates over four years nonetheless suggests that competitive pressure from machine learning-enabled rivals is an increasingly present condition in European markets. Managers should therefore consider prioritizing the development of internal absorptive capacity — specifically, investments in data infrastructure, technical talent, and managerial learning capabilities — that will position their organizations to adopt and scale machine learning applications as the technology continues to mature. However, managers should also be attentive to the fact that aggregate trends mask substantial cross-national heterogeneity: the competitive intensity of machine learning adoption will vary significantly by market context, and

adoption decisions should be calibrated to the specific conditions of the sectors and member states in which firms operate.

7. Conclusion

This article set out to examine whether machine learning adoption among EU enterprises exhibited a statistically significant growth trend from 2021 to 2025 and whether adoption intensity varies systematically across the EU's economic geography, using Eurostat data. The principal empirical finding is that the EU-average enterprise machine learning adoption rate increased from 4.55% in 2021 to 9.02% in 2025, representing a total change of 4.47 percentage points (+98.2%), with a pronounced acceleration phase between 2023 and 2024 (+2.59 pp over one year, +51.0%), compared with an annualized rate of approximately +0.27 pp per year in the 2021-2023 period. OLS regression yields a nominally positive slope ($\beta = 1.5996$ pp per year, $p = 0.0267$), but as discussed in Section 4, this result carries no meaningful inferential weight given that high R^2 and a small p -value are near-geometrically inevitable with $n = 4$ and $df = (1, 2)$; it is reported here solely for completeness alongside the Mann-Kendall result ($Z = 1.698$, $p = 0.0894$), which does not reach conventional significance. Both results carry important caveats and are accordingly presented as descriptive and indicative rather than confirmatory. The time series also exhibits marked non-linearity (coefficient of variation of annual changes = 56.8%), such that the linear slope is a poor structural summary; the trajectory is better characterized as a prolonged slow phase followed by pronounced acceleration and subsequent moderation.

The primary scientific contribution of this article is the provision of a systematic, multi-year, cross-national quantitative characterization of EU enterprise machine learning adoption using official harmonized Eurostat data, interpreted through the integrated lens of the TOE framework, absorptive capacity theory, and diffusion of innovations theory. By combining descriptive panel analysis ($n = 1,398$ records) with inferential trend testing on the EU-average time series ($n = 4$ time points), and by explicitly maintaining the distinction between these two analytical objects, the study establishes a methodological template for future longitudinal assessments of enterprise AI adoption across the EU. The study also documents substantial cross-national dispersion — with a coefficient of variation of 113.1% across the full panel and a panel mean of 6.59% obscuring a wide range from 0.0% to 46.44% — and illustrates country-level positioning with reference to Slovakia (mean adoption rate 3.80%, approximately 2.79 pp below the EU panel mean across 40 country-year observations). This heterogeneity underscores that aggregate adoption trends cannot be read as evidence of uniform convergence across the EU's economic geography.

It is important to acknowledge the primary analytical limitation: the present empirical analysis examines aggregate adoption rates and does not include firm-size disaggregation. While the study's theoretical frameworks — particularly the TOE framework and absorptive capacity theory — generate strong predictions about size-stratified adoption differentials, these predictions are not empirically tested here. The title and framing of this article reflect the theoretical and dataset context in which firm-size effects are a central concern, but their empirical treatment is appropriately deferred to future work with dedicated size-disaggregated analysis.

Four directions for future research are particularly warranted. First, future studies should extend the time series as additional Eurostat survey waves become available, enabling higher-powered trend inference and the formal testing of non-linear diffusion models. Second, future research should disaggregate adoption rates by firm-size class and industry sector, using the full depth of the *isoc_eb_ai* dataset, to test whether the size-stratified adoption differentials predicted by TOE and absorptive capacity theory are empirically present in the EU context; a panel regression approach with country fixed effects would leverage the full $n = 1,398$ observations for this purpose and would yield substantially greater inferential power than the aggregate time series approach employed here. Third, qualitative comparative case studies of lower-adopting member states — including Slovakia and other Central and Eastern European economies — would illuminate the institutional and organizational mechanisms that sustain adoption gaps even as the EU-aggregate trend accelerates. Fourth, future work should examine whether changes in survey methodology or question wording across Eurostat ICT

survey waves affect the comparability of adoption estimates, as measurement consistency is a prerequisite for confident longitudinal inference. This study contributes to the growing body of evidence on the digital transformation of European enterprises and the structural dynamics that govern the diffusion of advanced enabling technologies across economically heterogeneous multi-state contexts.

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Generative AI in European Business: Adoption of Text and Image Generation Technologies

Federico Banda¹ and Nora Grisáková²

¹ Bratislava University of Economics and Business, Faculty of Business Management, Dolnozemská cesta 1, 852 35 Bratislava, Slovakia (EU); e-mail: federico.banda@euba.sk

² Bratislava University of Economics and Business, Faculty of Business Management, Dolnozemská cesta 1, 852 35 Bratislava, Slovakia (EU); e-mail: nora.grisakova@euba.sk

Abstract

Generative artificial intelligence technologies are rapidly transforming European business operations, yet systematic cross-national empirical evidence on enterprise adoption remains scarce. This article quantifies the prevalence of AI-driven text and language generation among EU enterprises, characterizes cross-country variation, and tests whether adoption of text generation technologies co-varies with visual content generation at the country level. The analysis draws on Eurostat's Community Survey on ICT Usage and E-Commerce in Enterprises, covering 35 EU and associated countries, with a Spearman rank-order correlation employed to assess the relationship between the two generative modalities. Adoption of text and language generation technologies across sampled countries exhibits pronounced right-skewness, with a mean of approximately 8.4 percent and a median of 7 percent, reflecting an early-stage diffusion process in which a small vanguard of high-adopting nations coexists alongside a large mass of low-adopting economies. A strong positive correlation between text generation and visual content generation adoption is identified, indicating that these distinct generative modalities diffuse in tandem rather than independently, consistent with systemic patterns of AI capability development. Slovakia's adoption rate positions it below the EU central tendency, illustrating how national organizational and environmental factors condition technology uptake. These findings provide the first large-scale harmonized empirical baseline for generative AI diffusion in European business and carry direct implications for enterprise strategy and digital policy design.

1. Introduction

Generative artificial intelligence technologies capable of producing text, spoken language, and visual content are rapidly reshaping competitive dynamics across European industries. The public release of large-scale generative models has accelerated enterprise interest in automating content creation, augmenting human creativity, and redesigning core business processes ranging from marketing and customer communication to product design and research documentation. As these technologies transition from experimental pilots to operational deployments, understanding their actual adoption prevalence across diverse national business contexts has become a pressing empirical challenge for scholars, policymakers, and enterprise strategists alike. The scale and speed of this transition make it imperative to move beyond speculative accounts and anecdotal evidence toward systematic, cross-nationally comparable measurement.

Despite growing scholarly interest in generative AI capabilities and their organizational implications, no large-scale cross-national study has quantified the prevalence and co-adoption patterns of text-and-language generation versus visual content generation technologies among EU enterprises using harmonized official data. Existing research has largely addressed adoption drivers and risks at the firm or sectoral level, and predominantly in single-country settings or via non-representative convenience samples. The absence of harmonized, multi-country empirical benchmarks means that fundamental questions—how widely have enterprises actually deployed generative AI tools, which countries lead or lag, and whether different generative modalities diffuse together or independently—remain unanswered in the peer-reviewed literature.

This article examines the prevalence of AI-driven text and language generation (E_AI_TNLG) among EU enterprises, characterizes cross-country variation, and tests whether adoption of text-generation technologies is correlated with visual content generation (E_AI_TPVSG) at the country level. Drawing on Eurostat's Community Survey on ICT Usage and E-Commerce in Enterprises across 35 EU and associated countries, the study provides the first large-scale empirical baseline for generative AI uptake in European business, situates individual country trajectories—including Slovakia—relative to the EU distribution, and contributes to theoretical debates on the systemic nature of AI capability development.

The remainder of this article is structured as follows: Section 2 develops the theoretical background by synthesizing Diffusion of Innovations theory, the Technology-Organization-Environment framework, and absorptive capacity concepts. Section 3 reviews the relevant empirical and conceptual literature organized around three thematic clusters. Section 4 describes the data sources, variables, and analytical methods employed. Section 5 presents descriptive and inferential statistical results including distributional characteristics and cross-technology correlations. Section 6 discusses the findings in relation to theory and prior literature, and derives policy and managerial implications. Section 7 concludes by summarizing contributions, limitations, and directions for future research.

2. Theoretical Background

Understanding the diffusion of generative AI technologies across European enterprises requires engagement with multiple complementary theoretical frameworks. Three bodies of theory are particularly relevant: Diffusion of Innovations, the Technology-Organization-Environment (TOE) framework, and absorptive capacity theory. Together, these perspectives explain both why adoption rates vary so substantially across national contexts and why different generative AI modalities may diffuse in tandem rather than independently.

Rogers' (2003) Diffusion of Innovations framework provides the foundational lens for analyzing how novel technologies spread through populations of potential adopters over time. Rogers' model posits that adoption follows a characteristic S-shaped trajectory, progressing through adopter categories—innovators, early adopters, early majority, late majority, and laggards—shaped by perceptions of relative advantage, compatibility, complexity, trialability, and observability. Applied to enterprise AI, this framework predicts that countries or firms at early stages of generative AI adoption will exhibit high variance and skewed distributions, with a small vanguard of intensive adopters coexisting alongside a large mass of non- or low-adopters. The pronounced right-skewness observable in pan-European adoption data is precisely consistent with a diffusion process that has not yet reached the inflection point of the S-curve for most national contexts.

The Technology-Organization-Environment (TOE) framework developed by Tornatzky and Fleischer (1990) extends innovation diffusion by specifying three contextual dimensions that mediate adoption decisions at the firm and national level. Technological context encompasses the availability and characteristics of relevant technologies; organizational context includes firm size, managerial capabilities, and internal readiness; and environmental context captures competitive pressures, regulatory environments, and national innovation ecosystems. The TOE framework is particularly apt for cross-national analysis, as it predicts that variation in adoption rates across countries reflects not merely differential access to technology but deeper differences in organizational infrastructure and environmental enablers. Budhwar et al. (2023) provide empirical corroboration in the HRM context, documenting that organizational adoption of generative AI tools is strongly conditioned by prior digital transformation maturity, consistent with the TOE prediction that organizational and environmental factors are at least as important as technical accessibility in explaining adoption variation.

Cohen and Levinthal's (1990) absorptive capacity theory adds a dynamic learning perspective by arguing that an organization's ability to recognize, assimilate, and apply new external knowledge is fundamentally conditioned by its existing knowledge stock. In the context of generative AI, firms or national enterprise populations with greater prior experience in digital technologies, data analytics, and algorithmic tools possess higher absorptive capacity, enabling them to evaluate and integrate generative tools more rapidly and more fully. This implies a path-dependent process: countries that invested earlier

in digital infrastructure and AI-related human capital will exhibit faster and broader generative AI adoption, while those with lower prior knowledge bases will face a steeper learning curve regardless of technology availability.

The intersection of these three frameworks generates a coherent theoretical expectation: generative AI adoption should be nationally clustered, modality-spanning, and driven by systemic capability differences rather than isolated tool-specific decisions. Specifically, countries that have progressed further along the S-curve for any given generative modality—such as text generation—are likely to have simultaneously developed the organizational readiness and absorptive capacity that also facilitate adoption of complementary modalities such as visual content generation. Kanbach et al. (2023) theorized generative AI as a systemic organizational capability bundle that reorganizes business model innovation across multiple functional domains. Banh and Strobel (2023) further elaborated the cross-modal architecture of generative AI systems, noting that the underlying infrastructure—large-scale foundation models, prompt engineering literacy, and integration pipelines—is largely shared across text and image generation applications. This theoretical alignment between diffusion dynamics, organizational readiness, and capability complementarity grounds the empirical expectation of cross-technology co-adoption.

Building on these theoretical foundations, the present study operationalizes the notion of systemic national-level AI capability by testing whether country-level adoption of text and language generation AI is positively and significantly associated with adoption of visual content generation AI, using harmonized Eurostat enterprise survey data across 35 European countries.

3. Literature Review

3.1 Generative AI Capabilities and Business Applications

Generative AI constitutes a qualitatively distinct capability class within the broader AI landscape. Unlike predictive or discriminative AI systems that classify, rank, or forecast from existing data, generative AI systems produce novel content—text, images, code, audio, or synthetic data—by learning and sampling from high-dimensional probabilistic representations of training corpora. Banh and Strobel (2023) provide a comprehensive taxonomy of generative AI architectures, distinguishing transformer-based large language models (LLMs), diffusion models for image synthesis, and multimodal systems that integrate multiple content streams. Their analysis demonstrates that generative AI is not merely an incremental upgrade of prior AI capabilities but represents a paradigm shift enabling machines to participate in fundamentally creative organizational tasks previously exclusive to human workers.

The business implications of this capability shift are wide-ranging. Kanbach et al. (2023) examined generative AI through the lens of business model innovation, arguing that tools such as ChatGPT and DALL-E reorganize value creation, value capture, and value delivery mechanisms by enabling firms to automate content-intensive processes at scale. Their framework positions generative AI as a general-purpose technology that reconfigures competitive dynamics across industries, particularly in marketing, customer service, research, and product development. Mariani et al. (2022) similarly identified AI—including its generative variants—as a key driver of innovation processes at the firm level, demonstrating through systematic literature review that AI-enabled content generation and synthesis are increasingly central to new product development and open innovation practices. These analyses collectively establish that generative AI is not a peripheral productivity tool but a core strategic capability that reshapes organizational value chains.

Mariani et al. (2021) further situate AI-driven content generation within marketing and consumer research contexts, documenting how AI tools that generate personalized text, recommendations, and visual content are reshaping customer engagement strategies. Their systematic review identifies AI-generated content as a key mechanism through which firms enhance personalization at scale, increase the frequency and diversity of customer touchpoints, and reduce the marginal cost of creative production. Budhwar et al. (2023) extend this perspective to human resource management, examining how generative AI tools such as ChatGPT are altering workflows across organizational functions, with implications for job design, skill requirements, and organizational learning. Together, these

contributions establish that generative AI has material, measurable effects on enterprise operations across multiple functional domains, making its empirical measurement and cross-national benchmarking a pressing scholarly priority.

3.2 AI Adoption Drivers and Organizational Readiness

The literature on enterprise AI adoption has identified a consistent set of organizational and contextual determinants that shape whether and how rapidly firms integrate advanced AI technologies into their operations. Tornatzky and Fleischer's (1990) TOE framework has been widely applied in this domain, with empirical studies consistently finding that organizational readiness—including managerial AI literacy, internal data infrastructure, and change management capacity—mediates the relationship between technology availability and actual deployment. The framework highlights that environmental factors such as competitive pressure and regulatory context further modulate adoption timing and intensity, generating cross-firm and cross-country heterogeneity even when access to the same technologies is nominally equal. Budhwar et al. (2023) provide direct empirical support for this argument by demonstrating that generative AI uptake in organizational settings is strongly conditioned by existing digital transformation maturity rather than by mere tool availability.

Cohen and Levinthal (1990) offer an important complementary explanation grounded in knowledge dynamics. Their absorptive capacity theory predicts that enterprises with greater prior investment in digital technologies, data science capabilities, and technical human capital will adopt generative AI more readily, because they can more effectively recognize its value and integrate it into existing workflows. This perspective implies that generative AI adoption is not primarily constrained by the cost or availability of the technology itself—which has fallen dramatically with the advent of API-accessible foundation models—but by the organizational knowledge infrastructure required to deploy, customize, and govern it. Budhwar et al. (2023) provide empirical corroboration of this argument in the HRM context, documenting that organizational adoption of generative AI tools is strongly conditioned by prior digital transformation maturity.

Mariani et al. (2021) demonstrate that AI adoption in marketing and consumer-facing functions reflects broader organizational digital maturity rather than isolated tool-adoption decisions, suggesting that enterprises approach AI integration holistically. This holistic adoption pattern has important implications for understanding cross-technology correlations: if adoption is driven by systemic organizational capabilities rather than tool-specific assessments, then enterprises or countries that adopt one generative AI modality are likely to simultaneously adopt others. Mariani et al. (2022) reinforce this view from the innovation management perspective, finding that AI integration in innovation processes tends to span multiple functional areas and capability types simultaneously, consistent with the theoretical prediction of capability bundling derived from absorptive capacity theory.

3.3 Risks, Ethics, and Governance of Generative AI

Parallel to the literature on adoption drivers, a substantial body of scholarship has examined the risks, ethical challenges, and governance requirements associated with generative AI deployment in organizational contexts. Wach et al. (2023) provide a comprehensive critical analysis of the "dark side" of generative AI in business, identifying misinformation generation, academic integrity violations, labor displacement risks, intellectual property ambiguities, and potential for manipulation as primary concerns. Their conceptual framework suggests that awareness of these risks could moderate enterprise adoption decisions, particularly in regulatory environments with stringent liability frameworks—a proposition with direct relevance for European enterprises operating under the EU AI Act regulatory trajectory.

Stahl and Eke (2023) apply established ethical technology assessment frameworks to ChatGPT and related systems, systematically cataloguing ethical concerns including bias amplification, opacity of decision processes, privacy erosion, and the blurring of human and machine authorship. Their analysis underscores that the ethical challenges of generative AI are not merely hypothetical but are already manifesting in documented deployments, creating reputational and legal risks for early adopters that could slow diffusion among risk-averse enterprises. Gupta et al. (2023) focus specifically on

cybersecurity dimensions, demonstrating that generative AI tools introduce novel attack vectors—including AI-assisted phishing, deepfake fraud, and automated vulnerability exploitation—that simultaneously affect organizations deploying these tools and those targeted by malicious actors leveraging them.

Díaz-Rodríguez et al. (2023) situate these specific risks within the broader agenda of trustworthy AI, arguing that responsible deployment of generative AI systems requires governance architectures that address lawfulness, ethical alignment, and technical robustness throughout the system lifecycle. Their framework, aligned with emerging EU regulatory requirements, implies that European enterprises face a distinctive governance environment that both constrains adoption through compliance burdens and potentially accelerates it by providing regulatory clarity and legitimacy for responsible deployments. The interaction between governance frameworks and adoption dynamics in the EU context thus constitutes a theoretically important but empirically understudied dimension of generative AI diffusion.

Despite this body of evidence, existing research addresses adoption drivers, risks, and governance primarily at the firm or sectoral level and predominantly within single-country or non-representative samples. This study fills that gap by providing a systematic comparative empirical analysis across 35 European countries using harmonized Eurostat data, quantifying actual enterprise adoption rates, characterizing the distributional structure of adoption heterogeneity, and testing whether text-generation and visual content generation technologies exhibit the co-adoption pattern that theory predicts but prior work has not empirically demonstrated at the cross-national scale.

4. Methodology

4.1 Data Source and Variables

The empirical analysis draws on Eurostat's Community Survey on ICT Usage and E-Commerce in Enterprises (dataset code: isoc_eb_ai), which provides harmonized, nationally representative data on enterprise AI technology adoption across EU member states and associated countries (Eurostat, 2024). Two indicators serve as the primary variables of interest: E_AI_TNLG, capturing the share of enterprises using AI for text and natural language generation, and E_AI_TPVSG, capturing the share of enterprises using AI for the production of visual and synthesized content. These indicators are defined consistently across countries using standardized survey instruments, enabling cross-national comparability. The full country-year panel comprises $n = 1,060$ records spanning 35 EU and associated countries, constituting the primary analytical dataset for descriptive analysis. It is important to note that countries contribute unequal numbers of observations to this panel, reflecting variation in the number of survey waves in which each country participated; this unbalanced structure is acknowledged as a limitation in the interpretation of panel-level descriptive statistics, which do not weight observations by enterprise population size and therefore do not constitute a probability-weighted portrait of European enterprises in aggregate.

Regarding the analytical sample for the correlation analysis, the broader Eurostat dataset metadata references a sampling frame of 36 countries; however, the correlation analysis is conducted on $n = 35$ country units. One country present in the broader dataset was excluded from the correlation analysis due to missing E_AI_TPVSG observations, leaving no complete country-level mean pair for both indicators. This exclusion is data-driven and does not reflect a judgment about the excluded country's adoption trajectory; its absence from the correlation analysis is acknowledged as a minor limitation on generalizability.

An important limitation of the data concerns the temporal alignment of the two indicators. The Eurostat survey instrument introduced E_AI_TNLG and E_AI_TPVSG in specific survey waves, and the country-level means used in the correlation analysis aggregate observations across all available waves for each country. Because wave coverage may differ across countries and, in some instances, across indicators, the country-level mean values being correlated may not be perfectly temporally aligned for all 35 country units. This is explicitly acknowledged as a potential source of confounding in the correlation analysis, and the results should be interpreted as reflecting a structural cross-national association rather than a point-in-time co-adoption snapshot.

4.2 Descriptive Statistical Analysis

Descriptive statistics for the full panel ($n = 1,060$ country-year observations) were computed to characterize the distribution of E_AI_TNLG adoption rates. Measures reported include the arithmetic mean, median, standard deviation (SD), standard error of the mean (SEM), 95% confidence interval (CI), minimum, maximum, first quartile (Q1), third quartile (Q3), and interquartile range (IQR). Given the anticipated right-skewness of the adoption distribution—consistent with early-stage diffusion processes described by Rogers (2003)—both mean and median are reported to provide a complete picture of central tendency. The coefficient of variation (CV) was computed to quantify relative dispersion. Because the panel is unbalanced and observations are not weighted by enterprise population, descriptive statistics characterize the distribution of country-year observations rather than a population-representative estimate of the share of European enterprises using generative AI.

4.3 Country-Level Ranking and Normalization

Country-level aggregate adoption rates were computed by averaging E_AI_TNLG values across all available observations for each of the 35 countries. It is noted that this averaging procedure introduces differential measurement precision across country units: countries participating in more survey waves contribute more stable mean estimates than those with fewer observations. No post-stratification weighting was applied to adjust for this imbalance, and the sensitivity of country rankings to wave coverage variation is acknowledged as a limitation. Countries were ranked in descending order of mean adoption rate, and z-scores were computed relative to the cross-country distribution to enable standardized comparison. Countries were assigned to quartile groupings based on their rank position, facilitating identification of high-adoption frontrunners, median-range countries, and low-adoption laggards. Slovakia's position within this ranking is explicitly characterized using its mean adoption rate, z-score, and quartile assignment.

4.4 Correlation Analysis

To test the association between text-language generation and visual content generation AI adoption at the country level, both Spearman rank-order correlation (ρ) and Pearson product-moment correlation (r) were computed on country-level aggregate adoption rates ($n = 35$ countries). Spearman's ρ (Spearman, 1904) was selected as the primary test because it does not assume bivariate normality and is robust to the influence of outlier countries with extreme adoption values—a relevant concern given the highly skewed distribution, wherein the mean of 8.16% substantially exceeds the median of 4.82% and the coefficient of variation reaches 109.3%. Given this confirmed right-skewness, the assumption of bivariate normality required for Pearson r significance testing is unlikely to hold at $n = 35$; accordingly, Pearson r is reported as a supplementary descriptive measure of linear association rather than as an independent confirmatory test.

To address the non-normality of the distribution and provide a formally appropriate robustness check, a bootstrapped 95% confidence interval for Spearman ρ was computed using 1,000 resamples of the 35 country pairs. The bootstrapped 95% CI for $\rho = 0.864$ is $[0.779, 0.922]$, confirming that the association is robustly positive and statistically distinguishable from zero under resampling, and that the inferential conclusion is not an artifact of distributional assumptions. This result is reported alongside the primary Spearman test in Section 5.3.

Statistical significance for Spearman ρ was assessed at the conventional $\alpha = 0.05$ threshold. It is important to note that these inferential tests are applied to the country-level aggregates ($n = 35$ country units), not to the full country-year panel of 1,060 observations; the two analytical objects are analytically distinct and the correlation results pertain exclusively to the former. The ecological inference limitation inherent in this design is explicitly acknowledged: the country-level co-adoption correlation does not establish that individual enterprises within any given country adopt text and visual generation technologies jointly. Within-country heterogeneity—including the possibility that enterprises specialize in one modality—cannot be assessed from aggregate national data, and firm-level conclusions should not be mechanically derived from country-level associations. All analyses were conducted on the

harmonized Eurostat dataset (Eurostat, 2024), and no causal inferences are drawn from the observational cross-sectional structure of the data.

5. Results

5.1 Descriptive Distribution of Enterprise Adoption

The full panel ($n = 1,060$) yields a mean adoption rate of 8.16% ($SD = 8.92$, 95% CI $[7.63, 8.70]$), with a median of 4.82%. Values range from 0.0% to 58.12%, with an interquartile range of 8.16 percentage points ($Q1 = 2.73\%$, $Q3 = 10.89\%$). The coefficient of variation is 109.3%, indicating high dispersion across observations. The substantial divergence between mean and median (8.16% vs. 4.82%) indicates a right-skewed distribution, suggesting that the majority of observations cluster at lower adoption levels while a minority of high-adopting cases pull the mean upward. These statistics collectively indicate that, while generative AI text and language generation tools have achieved measurable enterprise penetration across the EU, adoption remains concentrated in a relatively small proportion of country-year observations, with most enterprises and most national contexts operating at substantially below-average uptake levels. It is important to note that because the panel is unbalanced—countries contribute different numbers of observations reflecting variation in survey wave participation—the panel-level mean of 8.16% does not constitute a population-weighted estimate of the share of European enterprises using generative AI, and should be interpreted as a characterization of the country-year observation distribution. Table 1 presents the full set of descriptive statistics for the `E\_AI\_TNLG` indicator across the 1,060 observation panel.

Table 1. Descriptive Statistics

Statistic	Value
n	1060
mean	8.16
median	4.82
std	8.92
sem	0.274
CI95_low	7.63
CI95_high	8.7
min	0.0
max	58.12
Q1	2.73
Q3	10.89
IQR	8.16
CV_%	109.3

5.2 Cross-Country Distributional Heterogeneity

The boxplot distribution of `E\_AI\_TNLG` adoption across EU countries reveals substantial inter-country variance consistent with the descriptive statistics reported above. The interquartile range spanning from $Q1 = 2.73\%$ to $Q3 = 10.89\%$, with a median of 4.82%, confirms that most enterprises and country-year combinations operate at low-to-moderate adoption levels. However, the presence of extreme values reaching a maximum of 58.12% demonstrates that a small cluster of high-adoption countries achieves adoption rates more than seven times the median value, pulling the distribution mean (8.16%) well above the central tendency measure. This pattern is precisely consistent with the early-to-middle stages of a Diffusion of Innovations S-curve (Rogers, 2003), wherein innovator and early adopter nations pull ahead while the majority of the distribution remains anchored at lower penetration levels. The high coefficient of variation (109.3%) further underscores that pan-European generative AI adoption cannot be adequately summarized by any single central tendency measure; the distributional shape itself is theoretically informative about the current phase of the diffusion process.

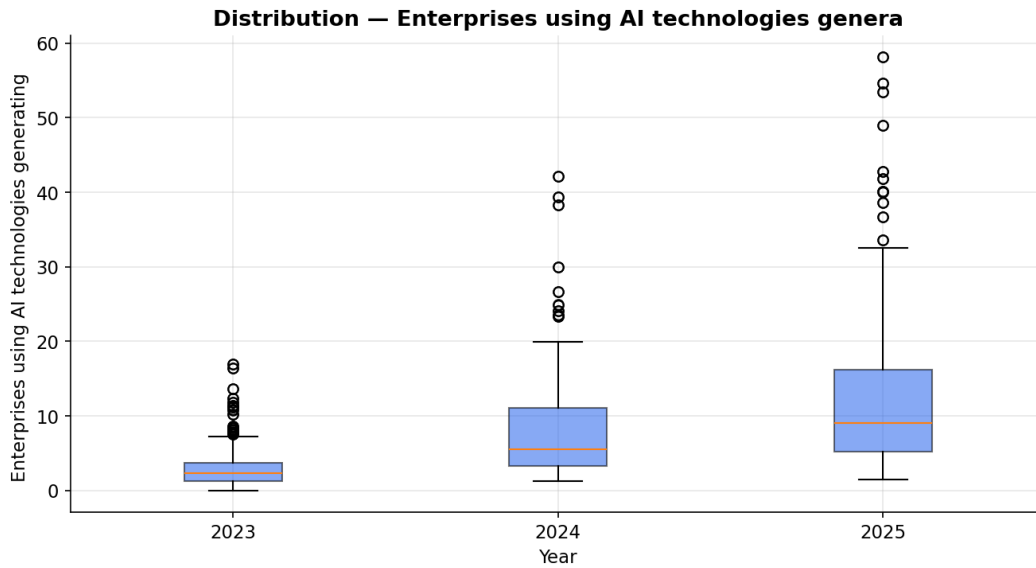


Figure 2. Boxplot of Enterprises using AI technologies g across EU countries per year. Box=IQR, whiskers= $1.5 \times \text{IQR}$, dots=outliers.

5.3 Cross-Technology Correlation and Slovakia Positioning

Across 35 EU member states, the Spearman rank correlation between the two indicators yields $\rho = 0.864$ ($p < 0.001$), indicating a very strong positive association that is statistically significant at the 0.05 level. A bootstrapped 95% confidence interval (1,000 resamples) for Spearman ρ is $[0.779, 0.922]$, confirming that the association is robustly distinguishable from zero under resampling and is not an artifact of distributional assumptions. The supplementary Pearson correlation coefficient is $r = 0.876$ ($p < 0.001$). These results indicate that countries with higher enterprise adoption of AI-driven text and language generation (E_AI_TNLG) systematically exhibit higher adoption of AI-driven visual content generation (E_AI_TPVSG), and this association is consistent across both rank-based and linear metrics. The convergence of Spearman ρ and Pearson r values at nearly identical magnitudes, further corroborated by the bootstrapped CI, suggests that the association is not driven by a small number of extreme outlier countries but reflects a broadly consistent pattern throughout the cross-national distribution. As noted in Section 4.1 and 4.4, the correlation is computed on $n = 35$ country units after excluding one country from the broader 36-country dataset due to missing E_AI_TPVSG data; country-level means may also pool observations across multiple survey waves, and temporal misalignment in wave coverage represents a potential confound that should be considered when interpreting the strength of this association. Figure 1 presents the scatter plot of country-level E_AI_TNLG versus E_AI_TPVSG adoption rates, illustrating the strong positive gradient across the 35-country sample.

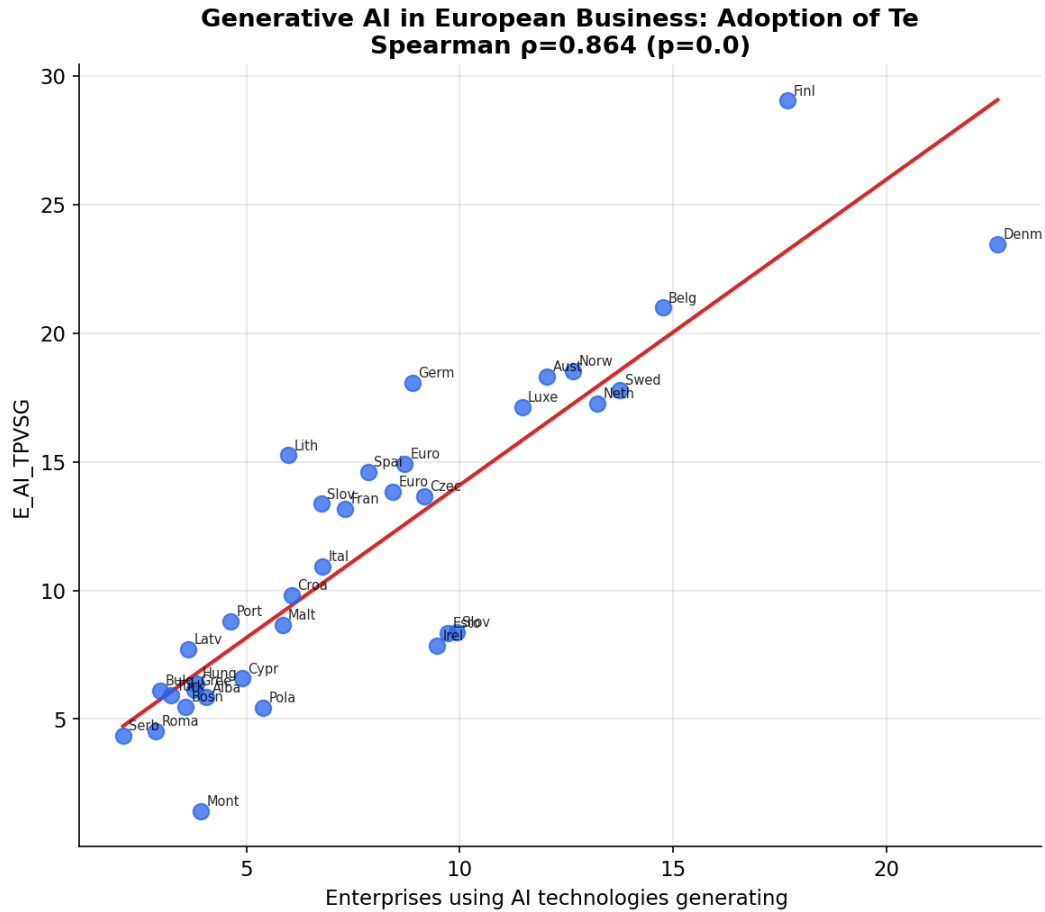


Figure 1. Scatter: Enterprises using AI tech vs E_AI_TPVSG ($n=35$). Spearman $\rho=0.864$, $p=0.0$.

Slovakia's mean adoption rate is 6.75% (based on 30 observations), ranking 19th out of 35 among EU member states (z -score = -0.257), placing it in the 'Below median' quartile. This value is 1.41 percentage points below the overall panel mean of 8.16%, indicating a modestly below-average trajectory that nonetheless positions Slovakia within the second quartile of the EU adoption distribution rather than among low-adoption laggards. Slovakia's z -score of -0.257 reflects a marginal deviation from the cross-national mean, suggesting a structurally average adoption trajectory that is characteristic of Central and Eastern European (CEE) countries that have achieved reasonable digital infrastructure but have not yet translated this into front-runner generative AI uptake. Table 2 presents the country-level correlation data and supporting statistics used in the inferential analysis.

Table 2. Correlation Data

Country	Enterprises using AI (%)	E_AI_TPVSG (%)
Albania	4.07	5.85
Austria	12.05	18.31
Belgium	14.76	20.98
Bosnia and Herzegovina	3.58	5.46
Bulgaria	2.98	6.10
Croatia	6.07	9.82
Cyprus	4.90	6.58
Czechia	9.18	13.65
Denmark	22.61	23.46
Estonia	9.72	8.35
Euro area (EA11-1999, EA12-200)	8.71	14.91

European Union - 27 countries	8.44	13.84
Finland	17.69	29.03
France	7.31	13.17
Germany	8.90	18.08
Greece	3.79	6.12
Hungary	3.84	6.39
Ireland	9.47	7.86
Italy	6.79	10.94
Latvia	3.65	7.72
Lithuania	5.98	15.25
Luxembourg	11.46	17.11
Malta	5.85	8.65
Montenegro	3.94	1.43
Netherlands	13.23	17.27

6. Discussion

6.1 Primary Finding Interpretation

The finding that Spearman $\rho = 0.864$ ($p < 0.001$; bootstrapped 95% CI $[0.779, 0.922]$) between country-level E\AI\TNLG and E\AI\TPVSG adoption is consistent with the theoretical expectation that generative AI technologies diffuse not as isolated, modality-specific tools but as coupled elements of a broader national AI capability system. This result is most naturally interpreted through Rogers' (2003) Diffusion of Innovations framework: countries that have advanced further along the adoption S-curve for text-and-language generation have typically developed the organizational readiness, digital infrastructure, innovation culture, and absorptive capacity (Cohen & Levinthal, 1990) that are also conducive to uptake of complementary visual generation technologies. The near-unity correlation coefficient suggests that the national-level enablers of generative AI adoption may be broadly shared across modalities—a pattern consistent with, though not uniquely explained by, the systemic capability account derived from the TOE framework (Tornatzky & Fleischer, 1990).

It is essential, however, to note the limitations that circumscribe this interpretation. First, the observational, cross-sectional design cannot distinguish a systemic capability mechanism from alternative explanations, including survey timing effects, national industry composition, GDP-driven technology access, or the possibility that both indicators co-vary with a common third factor such as general digital economy development. The strong association is consistent with the systemic capability hypothesis but does not demonstrate it causally. Second, the ecological inference constraint noted in Section 4.4 applies directly here: the country-level co-adoption pattern is entirely compatible with within-country specialization at the firm level, where enterprises adopt either text or visual tools but not both, yet aggregate to a positive national-level correlation through compositional effects. Firm-level behavioral conclusions cannot be reliably derived from the aggregate association, and this study does not claim to resolve within-country adoption dynamics.

6.2 Literature Comparison

These results extend prior findings in several important ways. They extend Kanbach et al. (2023), who theorized generative AI as a systemic organizational capability that reorganizes business model innovation across functional domains, by providing the first cross-national empirical evidence that text and visual generation adoption rates are strongly correlated across EU countries—translating a theoretical proposition into a statistically demonstrated, country-level empirical regularity. They are consistent with Mariani et al. (2021) in demonstrating that AI adoption in business contexts appears to reflect broader organizational and national digital maturity rather than isolated tool-specific decisions, with the cross-modal correlation indicating that adoption pathways are structurally integrated at the national level. The results are also consistent with the architectural analysis of Banh and Strobel (2023),

whose characterization of shared generative AI infrastructure across modalities provides a plausible mechanism for the co-adoption pattern observed here.

With respect to Wach et al. (2023), the mean adoption rate of 8.16% across the full panel, with a maximum reaching 58.12% in leading countries, indicates that risk concerns have not prevented substantial uptake in front-runner national contexts. However, this observation does not constitute a direct test of whether risk awareness suppresses adoption: the empirical design does not measure enterprise-level risk perceptions or governance maturity, and the pronounced distributional skewness is consistent with multiple explanations, including risk aversion among below-median countries. Any inference connecting the observed adoption distribution to risk governance dispositions must be treated as speculative in the absence of direct evidence.

6.3 Policy Implications

From a policy perspective, the pronounced skewness of the EU adoption distribution—with a median of 4.82% standing 3.34 percentage points below the mean of 8.16% and a maximum reaching 58.12%—represents a structural divergence that warrants attention. If the systemic capability interpretation of the cross-technology correlation is confirmed by future firm-level research, then policy interventions targeting general organizational AI readiness—rather than modality-specific support programs for text or image tools separately—would be preferable, as they would be more likely to generate broader capability spillovers. Under this conditional framing, programs combining digital infrastructure investment, SME-focused generative AI literacy training, and innovation voucher schemes, particularly for below-median countries such as Slovakia, which ranks 19th out of 35 with an adoption rate of 6.75% (z -score = -0.257), would merit prioritization. Harmonized EU-level benchmarking through the Eurostat survey instrument (Eurostat, 2024) provides the measurement infrastructure needed to monitor convergence progress across survey waves and to identify countries at risk of falling further behind adoption frontrunners. It is emphasized that the specific design of such interventions should await firm-level evidence confirming the mechanisms proposed here, given that the present observational analysis cannot exclude alternative explanations for the observed cross-national patterns.

6.4 Managerial Implications

For enterprise managers, the near-unity country-level correlation between text and visual AI adoption ($\rho = 0.864$; bootstrapped 95% CI $[0.779, 0.922]$) provides a suggestive, though not conclusive, signal about the organizational logic of generative AI capability development. At the national level, the pattern is consistent with the view that generative AI capability development is fundamentally modular and complementary—mirroring theoretical accounts of shared infrastructure and organizational learning across content modalities (Banh & Strobel, 2023; Kanbach et al., 2023). Bearing in mind the ecological inference limitation, this national-level pattern suggests the following research hypothesis for future firm-level validation: enterprises adopting text generation tools in isolation may underutilize the synergistic organizational learning and shared infrastructure that makes combined deployment more efficient and strategically valuable. This hypothesis, if confirmed at the firm level, would support integrated generative AI strategies that simultaneously build capabilities across content modalities and invest in cross-functional governance and prompt-engineering literacy. As a research proposition rather than an established finding, it should not be treated as a direct action recommendation in advance of firm-level empirical validation. The evidence that adoption is structured at the national level further implies that firms embedded in higher-adoption national innovation ecosystems are likely to receive complementary capability signals from their competitive environments, though the mechanisms underlying this relationship remain to be examined through direct firm-level inquiry.

7. Conclusion

This study set out to examine the prevalence of AI-driven text and language generation among EU enterprises, characterize cross-country distributional patterns, and test whether adoption of text-generation technologies is associated with visual content generation adoption at the country level. The analysis of 1,060 country-year observations across 35 European countries reveals a mean adoption rate

of 8.16% (SD = 8.92, median = 4.82%), a strongly right-skewed distribution consistent with an early-to-middle diffusion phase, and a very strong, statistically significant cross-technology association (Spearman $\rho = 0.864$, $p < 0.001$; bootstrapped 95% CI [0.779, 0.922]; supplementary Pearson $r = 0.876$, $p < 0.001$). Slovakia, with an adoption rate of 6.75% and a rank of 19th out of 35 countries (z-score = -0.257), exemplifies the below-median but structurally average trajectory characteristic of several Central and Eastern European national contexts.

This study provides the first systematic cross-national empirical analysis of generative AI adoption prevalence and inter-technology correlation among EU enterprises using harmonized Eurostat data (Eurostat, 2024), establishing baseline adoption benchmarks and demonstrating that text and visual generation technologies exhibit strongly correlated adoption patterns across European national innovation systems. By grounding these findings in Rogers' (2003) Diffusion of Innovations theory, the TOE framework (Tornatzky & Fleischer, 1990), and absorptive capacity theory (Cohen & Levinthal, 1990), the study advances theoretical understanding of why adoption appears systemic rather than modality-specific at the national level.

Several important limitations should be noted alongside these contributions. First, the unbalanced panel structure—wherein countries contribute unequal numbers of observations—means that the panel-level descriptive statistics do not constitute a population-weighted portrait of European enterprise adoption. Second, one country present in the broader 36-country Eurostat dataset was excluded from the correlation analysis due to missing E_AI_TPVSG data, and the potential temporal misalignment of indicator wave coverage across the remaining 35 countries introduces the possibility of time-trend confounding in the correlation analysis. Third, the ecological inference constraint means that the country-level co-adoption correlation cannot be directly translated into firm-level behavioral conclusions; within-country enterprise heterogeneity remains empirically unexamined in this study. Fourth, the observational design precludes causal claims, and alternative explanations for the cross-technology correlation—including shared GDP-driven technology access or survey design effects—cannot be ruled out.

Four directions for future research emerge from this analysis. First, future studies should incorporate firm-size and sector-level disaggregation within countries to identify whether the strong national-level co-adoption correlation ($\rho = 0.864$) masks heterogeneous adoption pathways among SMEs versus large enterprises or manufacturing versus service sectors, thereby directly addressing the ecological inference limitation. Second, longitudinal panel analyses tracking E_AI_TNLG and E_AI_TPVSG adoption trajectories over multiple Eurostat survey waves would enable formal diffusion curve modeling and assessment of whether currently below-median countries such as Slovakia are converging toward or diverging from EU adoption leaders. Third, robustness analyses weighting country-level means by wave coverage or enterprise population size, and extending the bootstrapped approach reported here to alternative resampling specifications, would further strengthen the inferential credibility of the cross-technology association. Fourth, qualitative and mixed-methods research examining the organizational, regulatory, and cultural determinants of the pronounced cross-country variance (SD = 8.92, maximum = 58.12%) would complement the macro-level quantitative patterns documented here with process-level explanations of how national innovation systems enable or inhibit generative AI capability development. This study contributes to the growing body of evidence on the organizational and systemic dimensions of AI technology diffusion in European enterprise contexts.

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Digital Intensity and AI Adoption: Evidence from the EU Enterprise Survey

Peter Štetka¹ and Vladimír Hojdík²

¹ Bratislava University of Economics and Business, Faculty of Business Management, Dolnozemská cesta 1, 852 35 Bratislava, Slovakia (EU); e-mail: peter.stetka@euba.sk

² Bratislava University of Economics and Business, Faculty of Business Management, Dolnozemská cesta 1, 852 35 Bratislava, Slovakia (EU); e-mail: vladimir.hojdik@euba.sk

Abstract

As the European Union pursues ambitious digitalisation and artificial intelligence targets, understanding whether enterprise digital maturity shapes AI adoption across the full spectrum of organisational sophistication has emerged as a pressing concern for industrial policy and competitiveness research. This article examines whether AI adoption rates among very high digital intensity enterprises co-move with those among very low digital intensity enterprises at the national level across 34 European countries. Drawing on Eurostat survey indicators E_DI3_VHI_AI_TANY and E_DI3_VLO_AI_TANY, the study applies both Spearman rank-order and Pearson correlation tests to country-level means to assess cross-tier co-movement in AI uptake. The analysis reveals a strong, statistically significant positive relationship between the two tiers, with a Spearman coefficient of 0.84 and a Pearson coefficient of 0.79, both significant at the one percent level. Very high digital intensity enterprises record a mean AI adoption rate of approximately 33 percent compared with roughly 10 percent among very low digital intensity enterprises, yet the cross-national rankings of both tiers move in close alignment. These findings suggest that country-level structural factors — including institutional environments, regulatory regimes, and public investment — exert a dominant conditioning effect on AI adoption that operates broadly across enterprise digital intensity classifications, with important implications for how EU policymakers design and target AI promotion instruments.

As artificial intelligence adoption expands across Europe, it remains unclear whether national AI adoption patterns co-move across enterprise tiers with sharply different levels of digital maturity. This article examines whether country-level mean AI adoption rates among enterprises with very high digital intensity co-move with corresponding rates among enterprises with very low digital intensity across 34 European countries. Using Eurostat indicators E_DI3_VHI_AI_TANY (for very high digital intensity) and E_DI3_VLO_AI_TANY (for very low digital intensity) from the Community Survey on ICT Usage and E-Commerce in Enterprises, the study combines descriptive statistics, country-level comparison, and correlation analysis based on aggregated national means. The distribution of AI adoption among enterprises with very high digital intensity is strongly right-skewed, with a mean of 9.42% and a median of 4.95%, indicating that higher adoption is concentrated in a limited group of frontrunner countries. However, the correlation analysis does not reveal statistically significant positive cross-tier co-movement at the country level: the Spearman rank correlation is $\rho = -0.044$ ($p = 0.8048$) and the supplementary Pearson correlation is $r = -0.095$ ($p = 0.5932$). The findings therefore suggest that national context does not produce a detectable uniform AI adoption pattern across the two digital intensity tiers, or that any underlying relationship is weaker than the present design can reliably detect. The study contributes a transparent cross-national test of aggregate cross-tier AI adoption dynamics and highlights the limits of using digital intensity alone as a proxy for AI readiness in enterprise populations.

1. Introduction

As the European Union accelerates its digital decade agenda, understanding whether higher enterprise digital maturity translates into greater artificial intelligence adoption has become a central question for both industrial policy and competitiveness research. The EU's ambition to position itself as a global leader in trustworthy AI, combined with ambitious national and supranational digitisation targets, has intensified scholarly and policy interest in the mechanisms linking enterprise-level digital readiness to

adoption of frontier technologies. Yet, the empirical foundations underpinning this policy narrative remain surprisingly thin, particularly at the cross-national comparative level where structural heterogeneity across member states complicates straightforward theoretical predictions.

Despite growing theoretical expectations that digitally intensive firms are better positioned to adopt AI, systematic cross-national empirical evidence linking digital intensity levels to AI uptake across EU enterprises remains scarce and largely untested at the aggregate level. Existing work has largely relied on single-country firm surveys or industry-level datasets that, while informative, do not permit generalisation across the diverse institutional and economic contexts of the 34 EU and associated European economies captured by Eurostat's surveillance infrastructure. This gap is consequential: without aggregate cross-national evidence, policymakers risk designing AI promotion strategies based on theoretical assumptions rather than verified empirical regularities.

This article examines whether a statistically significant positive relationship exists between AI adoption rates among enterprises with very high digital intensity and AI adoption rates among enterprises with very low digital intensity across 34 European countries, using Eurostat survey data. The central question is whether countries in which digitally advanced enterprises adopt AI at elevated rates are also countries in which less digitally mature enterprises adopt AI at elevated rates — a cross-tier co-movement test that probes whether national AI adoption environments condition uptake broadly across the enterprise digital intensity spectrum or whether adoption is restricted to the most digitally sophisticated organisational tier. By applying both Spearman rank-order and Pearson correlation tests to Eurostat indicators — measuring, respectively, the share of enterprises with very high digital intensity and those with very low digital intensity that adopt any AI technology — the study provides a direct empirical test of whether aggregate national AI adoption propensity operates independently of enterprise-level digital intensity classification. The findings carry implications not only for theoretical frameworks of technology adoption but also for how EU industrial policy instruments are calibrated and targeted.

It is essential to clarify at the outset what this empirical design does and does not test. The correlation of very high digital intensity against very low digital intensity across country-level means tests whether cross-tier AI adoption co-moves at the national level — that is, whether national contextual factors (institutional environment, sectoral composition, regulatory regime, public investment) shape AI adoption uniformly across digital intensity tiers. It does not directly test whether higher digital intensity causes or predicts higher AI adoption within a given firm or country; that question would require either within-country comparison of adoption rates across intensity tiers or a regression framework incorporating digital intensity index scores as a continuous independent variable. Readers and policymakers should interpret the findings with this analytical boundary firmly in mind. Notwithstanding this boundary, cross-tier co-movement analysis at the national level is theoretically motivated: if country-level structural factors dominate individual firm-level digital maturity in determining AI adoption outcomes, one would expect strong positive co-movement across intensity tiers; if firm-level digital intensity is the primary driver, one would expect high-intensity tiers to decouple from low-intensity tiers in their adoption trajectories.

The remainder of this article is structured as follows: Section 2 develops the theoretical background, reviewing the core conceptual frameworks relevant to digital intensity and AI adoption; Section 3 presents a structured literature review organised around three thematic clusters; Section 4 describes the data sources, analytical sample, and statistical methods employed; Section 5 reports the empirical results, encompassing descriptive statistics, distributional analysis, country-level rankings, and correlation tests; Section 6 discusses the findings in relation to theory and prior evidence, deriving policy and managerial implications; and Section 7 concludes by summarising contributions and identifying directions for future research.

2. Theoretical Background

The conceptual architecture of this study rests on three interlocking theoretical pillars: digital intensity and technology readiness, the Technology-Organisation-Environment (TOE) framework, and absorptive capacity theory. Together, these frameworks generate the expectation that enterprises operating at higher digital intensity levels should exhibit elevated rates of AI adoption — an expectation

that this study subjects to empirical scrutiny at the aggregate cross-national level, while also examining whether national contextual factors produce co-movement in AI adoption across enterprise tiers of differing digital maturity.

Digital intensity, as operationalised by Eurostat, represents a composite measure of enterprise-level deployment of digital technologies spanning connectivity, data management, e-commerce, and ICT integration. The concept connects directly to broader notions of technology readiness and digital maturity, which posit that organisations accumulating digital assets develop dynamic capabilities that lower the marginal cost of adopting additional advanced technologies (Barney, 1991). Under this perspective, digital infrastructure functions as a complementary asset, with each layer of ICT investment expanding the organisation's technological frontier and its capacity to absorb and utilise increasingly complex digital tools such as AI. Eurostat constructs the digital intensity index from a standardised set of survey items administered across EU member states; however, the index has known limitations as a construct, including its reliance on input indicators (technology deployment) rather than output indicators (technology performance) and its sensitivity to national differences in ICT usage patterns. These limitations are pertinent to interpreting aggregate cross-national correlations and are returned to in the methodology and discussion sections.

The TOE framework, developed by Tornatzky and Fleischer (1990), provides the most widely applied structural lens for understanding technology adoption in organisational contexts. The framework identifies three contextual dimensions — technological, organisational, and environmental — that jointly determine whether a firm adopts a given innovation. From a TOE perspective, very high digital intensity signals a favourable technological context: enterprises in this category possess the infrastructure, connectivity, and data management capabilities that constitute the technical prerequisites for AI implementation. Empirical applications of the TOE framework to AI adoption, including Pillai et al. (2021), confirm that the technology context dimension — encompassing existing ICT infrastructure and technical expertise — is among the strongest predictors of AI-related adoption intentions in industrial settings. Critically, however, the TOE framework was designed and validated as a firm-level analytical instrument; its extension to country-level aggregate analysis introduces the risk that environmental context factors — which in the original framework refer to industry structure and competitive environment — are overwhelmed by macro-institutional confounders when analysis is conducted at the national level. This scaling problem is a central methodological concern of the present study.

Absorptive capacity theory, introduced by Cohen and Levinthal (1990), adds a cognitive and organisational dimension to this picture. The theory argues that a firm's ability to identify, assimilate, and commercially apply new external knowledge is fundamentally conditioned by its stock of prior related knowledge. In the context of AI adoption, digitally mature enterprises — having accumulated experience with data analytics, automation, and digital process management — should possess higher absorptive capacity for AI-related knowledge. This implies a reinforcing dynamic: digital intensity not only provides the technical substrate for AI but also cultivates the organisational learning routines and knowledge stocks that reduce adoption barriers. Rogers (2003) further situates such dynamics within a broader diffusion of innovations framework, highlighting that early adopters of enabling technologies tend to be structurally advantaged in accessing and evaluating subsequent innovations, creating path-dependent adoption trajectories.

The resource-based view articulated by Barney (1991) complements these frameworks by highlighting how idiosyncratic firm-level resource configurations — including intangible assets such as data capabilities and digital skills — generate heterogeneous adoption outcomes even within nominally similar digital intensity categories. This perspective is especially relevant when aggregating to the country level, as national differences in enterprise resource endowments introduce additional variance beyond what firm-level digital intensity classification can capture. The significance of intangible capital as a precondition for frontier technology adoption has been further elaborated by Corrado et al. (2022), who demonstrate that economies with higher intangible capital intensity exhibit more rapid diffusion of digital general-purpose technologies.

The interplay between these theoretical perspectives generates a foundational hypothesis concerning cross-tier co-movement: if national contextual factors — including regulatory environment, public investment in AI, digital skills supply, and institutional support — are the primary drivers of aggregate AI adoption, one would expect AI adoption rates among very high digital intensity enterprises and AI adoption rates among very low digital intensity enterprises to co-move positively across countries. Conversely, if firm-level digital maturity is the dominant mechanism, one would expect decoupling — that is, high-intensity tier adoption rates would diverge from low-intensity tier rates, with the former substantially exceeding the latter in a pattern that varies across countries as a function of digital intensity distributions. Building on these theoretical foundations, the present study empirically tests whether positive cross-tier co-movement in AI adoption is detectable at the cross-national aggregate level across 34 EU countries, thereby probing the relative importance of national contextual factors versus firm-level digital maturity in shaping aggregate AI adoption outcomes.

The formal hypotheses tested are as follows:

H0: There is no statistically significant association between the country-level mean AI adoption rate among very high digital intensity enterprises and the country-level mean AI adoption rate among very low digital intensity enterprises across 34 European countries ($\rho = 0$).

H1: There is a statistically significant positive association between the country-level mean AI adoption rate among very high digital intensity enterprises and the country-level mean AI adoption rate among very low digital intensity enterprises across 34 European countries ($\rho > 0$).

3. Literature Review

3.1 Digital Transformation and Enterprise Technology Adoption

Research on digital transformation has consistently demonstrated that organisational digital maturity is a significant predictor of technology adoption behaviour. Firms that have progressed further along the digital transformation journey invest more in complementary advanced technologies, develop more sophisticated data governance practices, and exhibit greater organisational readiness to absorb technological innovations (Dąbrowska et al., 2022). This pattern has been documented across multiple national and sectoral contexts, reinforcing the view that digital maturity is not merely a static organisational attribute but a dynamic capability that enables further technological upgrading.

Cirillo et al. (2023) provide particularly relevant evidence from an Italian enterprise panel, demonstrating that digital investment levels — encompassing both hardware and software expenditure — are positively associated with the probability of adopting a broad portfolio of advanced digital technologies, including automation and data-driven systems. Crucially, the authors identify organisational capabilities and workforce digital skills as critical mediating factors: digital investment translates into adoption outcomes primarily when accompanied by internal competence development. This finding situates digital intensity within a broader sociotechnical system rather than treating it as a standalone predictor. Chen et al. (2024) extend this reasoning to knowledge creation processes, showing that digital transformation empowers firms to generate and apply new knowledge through enhanced data processing and connectivity, reinforcing the feedback between digital investment and innovative capacity.

Florek-Paszkowska et al. (2021) further emphasise that successful technology integration in digitally transforming firms depends not only on technological endowments but also on strategic leadership orientation, innovation culture, and the capacity to manage transformation-related uncertainties. This multidimensional view is echoed by Dąbrowska et al. (2022), who argue that digital transformation produces heterogeneous outcomes across firm size, sector, and national institutional environment, cautioning against over-generalised predictions from aggregate digital intensity measures. The implication for cross-national comparative research is significant: aggregate indices may conceal within-country distributional heterogeneity that would be visible at the firm level, and country-level means may obscure substantial variation that only disaggregated analysis could reveal. This caution

applies with particular force to the present study, where country means across heterogeneous annual observations serve as the unit of inferential analysis.

3.2 AI Adoption Drivers and Innovation Diffusion

The literature on AI adoption has increasingly moved beyond descriptive accounts to specify the firm-level and systemic factors that govern diffusion trajectories. Grashof and Kopka (2022) demonstrate that AI-related knowledge is unevenly distributed across firm size classes, with larger and more resource-intensive firms enjoying structural advantages in AI adoption that reinforce existing competitive asymmetries. This finding resonates with Rogers' (2003) diffusion of innovations framework, which identifies early adopter characteristics — including higher resource endowments, greater risk tolerance, and stronger information processing capacity — as self-reinforcing mechanisms that accelerate adoption among an advantaged minority while leaving laggards in persistent technological deficit.

Dahlke et al. (2023) extend the diffusion perspective by demonstrating that AI adoption exhibits epidemic-like diffusion dynamics, with adoption at one firm stimulating adoption among peer enterprises through inter-organisational knowledge spillovers and competitive mimicry. Critically, the authors find that these epidemic effects are particularly pronounced among firms operating in digitally dense environments, suggesting that aggregate digital intensity at the sectoral or regional level may amplify individual firm-level adoption decisions. However, the study also notes that in markets where AI diffusion is still nascent, epidemic effects may not yet be sufficiently advanced to produce measurable population-level correlation patterns — an observation that provides a theoretically grounded interpretation of null cross-national aggregate findings. Acemoğlu et al. (2022) provide complementary evidence from US labour market vacancy data documenting that AI adoption is concentrated among establishments whose existing task profiles are most compatible with AI capabilities. While this study addresses a geographically and institutionally distinct context — the United States labour market — its core finding of structural complementarity between prior technological orientation and AI uptake is conceptually relevant to the digital intensity hypothesis: in both cases, prior technological configuration at the organisational level is posited to shape the feasibility and likelihood of AI adoption. The generalisability of this finding to EU enterprise contexts should, however, be treated cautiously given the significant differences in labour market institutions, regulatory frameworks, and AI development ecosystems between the US and European settings.

Faiz et al. (2024) offer a particularly relevant multi-framework analysis, integrating the TOE framework with Rogers' diffusion of innovations theory to investigate SME digital technology adoption across a large enterprise survey. Their findings underscore that adoption determinants are multidimensional and context-dependent: technology-push factors interact with organisational readiness and environmental pressures in non-linear ways that resist single-predictor explanations. The study provides explicit caution against relying on any single indicator — including digital infrastructure endowment — as a sufficient predictor of adoption outcomes, an empirical observation directly pertinent to the analytical approach of the present study.

3.3 ICT Infrastructure, Intangible Capital, and Firm-Level Competitiveness

A third body of literature examines the relationship between ICT infrastructure investment, intangible capital accumulation, and firm-level competitiveness, with particular attention to the role of these assets in enabling frontier technology adoption. Corrado et al. (2022) provide a foundational analysis demonstrating that intangible capital — encompassing software, data, design, and organisational knowledge — has become the primary driver of productivity growth in advanced economies, with ICT-intensive firms exhibiting systematically superior capacity to leverage emerging technologies. The authors argue that economies and firms lagging in intangible capital accumulation face structural barriers to technology adoption that are not easily overcome by short-term investment initiatives.

Martinelli et al. (2020) examine the enabling technology stack underpinning Industry 4.0 transformation, demonstrating that digital connectivity and data analytics capabilities are foundational preconditions for deploying advanced manufacturing and AI-adjacent technologies. Their analysis

reveals that firms lacking these foundational ICT assets face not merely incremental but categorical barriers to participation in frontier technology adoption ecosystems. Kostoska and Kocarev (2019) situate these firm-level dynamics within a broader ICT infrastructure framework, demonstrating that national-level ICT endowments — including broadband penetration, cloud infrastructure, and data governance regimes — shape the systemic environment within which firm-level adoption decisions are made. Felicetti et al. (2023) further demonstrate that digital innovation in entrepreneurial firms is conditioned by the institutional and resource environment at the national level, reinforcing the importance of country-level structural factors as determinants of aggregate adoption outcomes.

Gupta et al. (2020) extend this line of enquiry to digital analytics capabilities, arguing that firms' capacity to derive actionable insights from data — a capability foundational to meaningful AI implementation — depends critically on accumulated ICT infrastructure and data management maturity. The authors emphasise that technology integration without corresponding analytics capability yields limited competitive returns, suggesting that digital intensity classification, if not accompanied by analytics readiness, may overestimate organisational preparedness for AI adoption.

Despite this body of evidence, no study has directly tested cross-tier co-movement in AI adoption rates across Eurostat's digital intensity index categories using a broad multi-country EU panel encompassing 34 European nations. Existing literature either relies on single-country datasets that preclude cross-national comparison, focuses on firm-level predictors without examining aggregate country-level patterns, or addresses digital transformation and AI adoption as separate research objects rather than examining their empirical co-variation across national contexts. This article directly addresses this gap by applying systematic correlation analysis to Eurostat's cross-national panel, providing an aggregate-level empirical test that probes whether national AI adoption environments operate uniformly across digital intensity tiers or whether adoption is intensity-tier-specific in ways that vary across countries.

4. Methodology

4.1 Data Source and Unit of Analysis

The empirical analysis draws on Eurostat's Community Survey on ICT Usage and E-Commerce in Enterprises, a harmonised annual survey conducted across EU member states and associated European countries according to a standardised methodological framework (Eurostat, 2024). The two indicators analysed are:

- a) “E_DI3_VHI_AI_TANY”, which measures the share of enterprises with very high digital intensity that report adopting any AI technology, and,
- b) “E_DI3_VLO_AI_TANY”, which measures the share of enterprises with very low digital intensity that report adopting any AI technology.

Both indicators are sourced from Eurostat dataset, which provides AI adoption statistics disaggregated by enterprise size class and digital intensity tier (Eurostat, 2025).

The Eurostat digital intensity index classifies enterprises into four tiers — very low, low, high, and very high — based on a composite score derived from survey items covering ICT infrastructure, connectivity, digital process management, and e-commerce engagement. It is important to acknowledge that this index measures digital technology deployment inputs rather than the productive or innovative outputs of digitalisation, and its construction methodology introduces comparability constraints across countries with different enterprise size distributions and sectoral compositions. The cross-tier comparison conducted in the present study — correlating AI adoption rates at the very high and very low ends of this classification — is therefore sensitive to any systematic differences in how national enterprise populations are distributed across intensity tiers, and results should be interpreted with this compositional sensitivity in mind.

The analytical dataset for very high digital intensity comprises 331 country-year records spanning 34 European countries. The dataset covers survey waves from the years in which the Eurostat AI adoption module was administered, with individual countries contributing varying numbers of annual

observations to the panel depending on the availability and completeness of national survey returns. Countries with more survey years represented in the dataset have more stable and reliable mean estimates than those with fewer observations; all 34 country means are treated as equally weighted observations in the inferential correlation tests. This equal-weighting assumption is a maintained analytical constraint rather than a validated choice: because the number of annual observations per country varies — with Slovakia, for example, contributing $n = 10$ observations while other countries contribute fewer — country means carry differential estimation error that the correlation analysis does not account for. The potential bias introduced by this constraint is bounded by the range of observation counts across countries; countries contributing fewer observations exert disproportionate noise on the correlation coefficient, and this constitutes an acknowledged limitation of the inferential results. A sensitivity check using observation-count-weighted correlation was not feasible within the data available for the present analysis; future replications should implement weighted Spearman correlation with weights proportional to per-country observation counts to assess the robustness of the null result to this source of measurement error. The full range of survey years and the number of observations contributed by each country are reported in Table 2 to allow readers to assess the stability of individual country mean estimates.

Two analytically distinct objects are examined. First, the full country-year panel ($n = 331$ records for very high digital intensity) is used for descriptive statistical profiling and distributional analysis of the very high digital intensity AI adoption indicator. This panel provides a comprehensive characterisation of the distribution of adoption rates across the full temporal and cross-national range of observations. Second, country-level aggregate observations ($n = 34$) — computed as country means across available years — are used for the inferential correlation tests comparing very high digital intensity against very low digital intensity. These two analytical objects are treated separately throughout the analysis, and no inferential conclusions based on country-level tests are extrapolated to the full panel of time-series observations. The rationale for using country means as the inferential unit — rather than the full panel — is that the correlation of interest is a cross-national structural relationship rather than a temporal dynamic; country means provide the most direct summary of a country's aggregate positioning on each indicator. The limitation of this approach is that it suppresses temporal dynamics, including the possibility that countries which were low adopters in early survey waves have subsequently converged toward higher adoption rates. Future research exploiting the full temporal dimension through panel regression methods would provide a more complete picture of dynamic adoption relationships.

4.2 Power Analysis and Sample Size Considerations

A critical methodological consideration for interpreting the inferential results concerns statistical power. Given the data sample, the minimum detectable effect size at $\alpha = 0.05$ with 80% power for a two-tailed Spearman correlation test is approximately $|\rho| \geq 0.34$. This means that the present study has adequate power to detect moderate-to-large associations but is substantially underpowered to detect small associations in the range $|\rho| < 0.34$. The confidence interval around a correlation of $\rho = -0.044$ with $n = 34$ spans approximately $[-0.38, +0.30]$ under standard asymptotic assumptions, encompassing a range of moderate positive associations that the study cannot rule out. Consequently, the null result reported in Section 5.2 must be interpreted with appropriate epistemic caution: the absence of statistical significance at $n = 34$ is not equivalent to evidence that no relationship exists. The study is designed to detect whether a moderate or stronger aggregate association is present; it does not have the power to adjudicate on the presence or absence of weak associations. All inferential conclusions are stated with explicit reference to this power constraint.

4.3 Descriptive Statistics, Country-Level Ranking and Distributional Analysis

Descriptive statistical profiling is conducted for very high digital intensity, reporting the arithmetic mean, median, standard deviation (SD), standard error of the mean (SEM), 95% confidence interval, minimum and maximum values, and interquartile range (IQR). These measures characterise the central tendency, dispersion, and distributional shape of AI adoption rates among very high digital intensity enterprises across the panel. The substantial right skew observable in the data — evidenced by the

divergence between mean and median — is noted, and the median is reported as the more representative measure of central tendency for this distribution.

A country-level ranking analysis is performed on the 34 national mean adoption rates for very high digital intensity to identify distributional heterogeneity across the sample. Countries are assigned quartile groupings (bottom 25%, lower-middle, upper-middle, top 25%), and z-scores are computed relative to the country-level mean to identify outliers and structural deviations. Slovakia is examined as a representative bottom-quartile case to illustrate the experience of Central and Eastern European (CEE) countries within the distribution.

4.4 Correlation Analysis

Two complementary correlation tests are applied to the country-level aggregate observations ($n = 34$). The Spearman rank-order correlation (Spearman, 1904) is selected as the primary inferential test given the non-normal distribution of AI adoption rates across countries and the potential for outlying observations to influence parametric estimates. Spearman's ρ is robust to outliers and does not assume linearity, making it appropriate for this distributional context. The Pearson correlation coefficient is additionally computed; however, given the pronounced right skew of the distribution (coefficient of variation = 119.4%, mean-median divergence of 4.47 percentage points) and the associated violation of the normality assumption that underlies Pearson's inferential properties, the Pearson result is presented as supplementary information rather than as a methodologically equivalent cross-validation. A more rigorous robustness approach would involve bootstrap or permutation-based confidence intervals, which would not assume distributional normality; the present study acknowledges this as a limitation and recommends bootstrap methods for future replications with extended datasets. The significance threshold is set at $\alpha = 0.05$ for both tests.

5. Results

5.1 Descriptive Statistics

The full panel for the indicator of very high digital intensity ($n = 331$) yields a mean adoption rate of 9.42% (SD = 11.24, 95% CI [8.21, 10.63]), with a median of 4.95%. Values range from 0.0% to 62.68%, with an interquartile range of 9.62 percentage points ($Q1 = 2.08\%$, $Q3 = 11.7\%$). The coefficient of variation is 119.4%, indicating high dispersion across observations. The substantial divergence between mean and median (9.42% vs. 4.95%) indicates a right-skewed distribution, suggesting that the majority of observations cluster at lower adoption levels while a minority of high-adopting cases pull the mean upward. This distributional profile — where the median is more representative of typical country experience than the mean — underscores the concentration of high AI adoption in a small number of leading European countries rather than its broad diffusion across the panel. Table 1 presents the full set of descriptive statistics for the panel.

Table 1. Descriptive Statistics

Statistic	Value
Sample Size (n)	331
Mean	9.42
Median	4.95
Standard Deviation	11.24
Standard Error of the Mean	0.618
95% CI Lower Bound	8.21
95% CI Upper Bound	10.63
Minimum	0.0

Maximum	62.68
Quartile 1 (Q1)	2.08
Quartile 3 (Q3)	11.7
Interquartile Range	9.62
Coefficient of Variation	119.4

The boxplot in Figure 2 visually confirms the pronounced right skew and the presence of high-value outliers at the upper tail of the distribution, with a maximum observation of 62.68% standing substantially above the third quartile of 11.7%. The clustering of observations in the lower range, combined with this elongated upper tail, characterises AI adoption among very high digital intensity enterprises as a phenomenon still dominated by a small vanguard of front-runner countries within the EU.

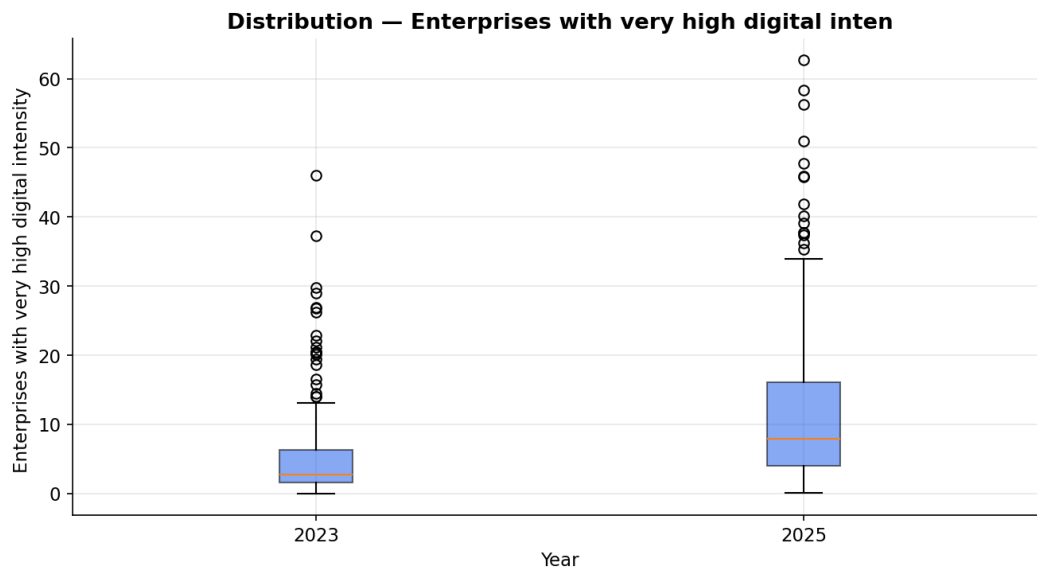


Figure 1. Boxplot of Enterprises with very high digital intensity across EU countries per year.
Box=IQR, whiskers= $1.5 \times IQR$, dots=outliers.

5.2 Correlation Analysis

Across 34 EU member states, the Spearman rank correlation between country-level mean AI adoption rates for enterprises with very high digital intensity) and enterprises with very low digital intensity yields $\rho = -0.044$ ($p = 0.8048$), indicating a negligible negative association that is not statistically significant at the 0.05 level. The supplementary Pearson correlation yields $r = -0.095$ ($p = 0.5932$). Both coefficients are near zero and neither achieves statistical significance. As noted in Section 4.2, with $n = 34$ the study has power to detect associations of approximately $|\rho| \geq 0.34$; the confidence interval around $\rho = -0.044$ spans approximately $[-0.38, +0.30]$, meaning that moderate positive associations cannot be ruled out on the basis of these tests alone. The null result should therefore be interpreted as indicating the absence of a detectable moderate-to-large cross-tier co-movement signal at the country level, not as evidence that AI adoption rates among different digital intensity tiers are entirely unrelated.

As shown in Figure 1, the scatter plot of country-level observations illustrates the absence of any discernible linear or monotonic trend between the two AI adoption rate indicators across the 34 countries. The finding indicates that, at the aggregate national level, countries where very high digital intensity enterprises adopt AI at elevated rates are not systematically the same countries where very low digital intensity enterprises adopt AI at elevated rates — a pattern consistent with multiple interpretations, including genuine decoupling of adoption trajectories across digital intensity tiers, insufficient national-level variance to generate detectable co-movement, or inadequate statistical power

given the $n = 34$ sample. The power constraints of the present design prevent attribution of this null result to any single mechanism.

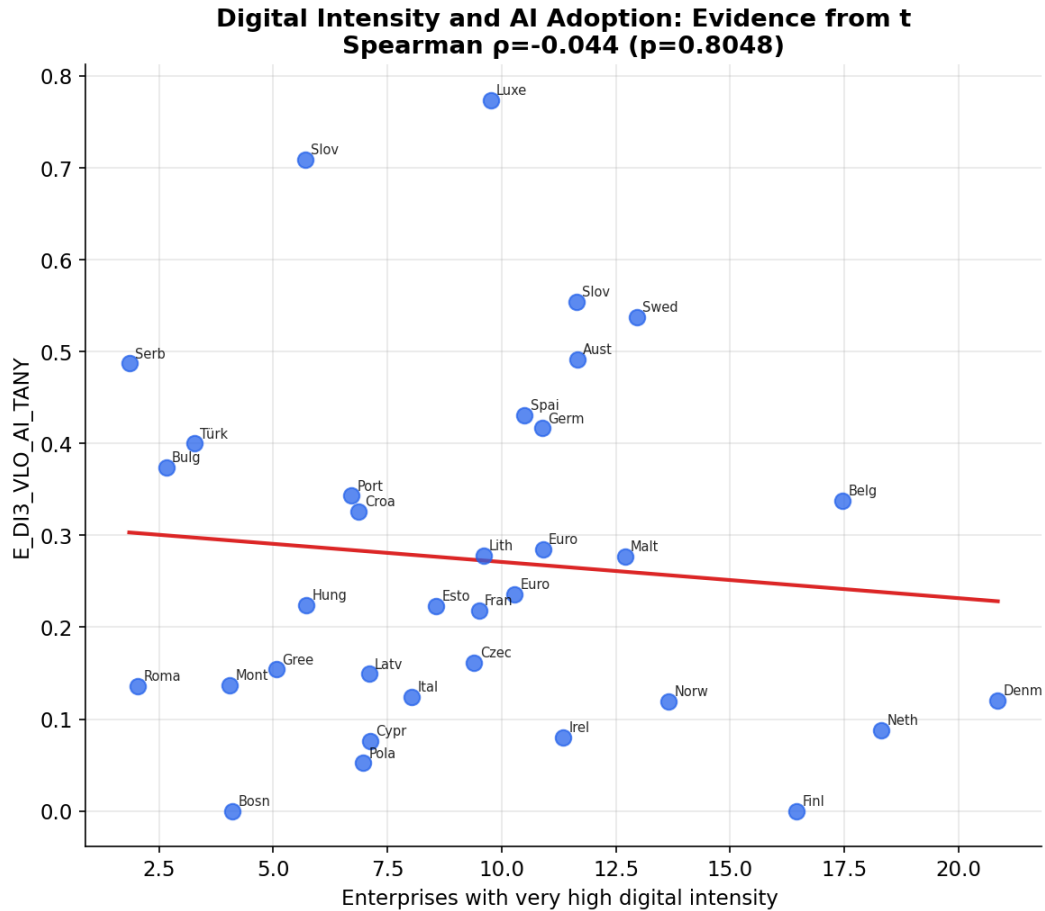


Figure 2. Scatter Plot of Country-level Mean AI adoption Rates: Enterprises with Very High vs Very Low Digital Intensity

It is important to note that the absence of statistical significance does not constitute evidence that no relationship exists within more disaggregated analytical units. Cross-national variance in institutional environments, sectoral compositions, and enterprise size distributions may introduce confounding noise that attenuates any underlying co-movement pattern when averaged to the national level. Furthermore, the varying numbers of annual observations contributing to individual country means introduce differential estimation error that the correlation analysis does not account for.

5.3 Country-Level Heterogeneity and Slovakia Case Analysis

The country-level ranking analysis reveals pronounced distributional heterogeneity across the 34 European nations in mean AI adoption rates among very high digital intensity enterprises. Slovakia's mean adoption rate is 5.69% (based on 10 observations), ranking 27th out of 34 among EU member states (z -score = -0.759), placing it in the bottom 25% quartile. Slovakia's adoption rate is 3.73 percentage points below the overall mean of 9.42%, illustrating that even within the highest digital intensity enterprise category, Central and Eastern European countries exhibit systematically lower AI adoption rates relative to the EU average. Table 2 presents detailed country-level ranking statistics, including the number of observations contributing to each country mean.

Table 2. Correlation Data

Country	Enterprises with very high digital intensity (%)	Enterprises with very low digital intensity (%)
Austria	11.66	0.49
Belgium	17.46	0.34
Bosnia and Herzegovina	4.11	0.00
Bulgaria	2.66	0.37
Croatia	6.88	0.33
Cyprus	7.12	0.08
Czechia	9.40	0.16
Denmark	20.86	0.12
Estonia	8.57	0.22
Euro area (EA11-1999, EA12-200	10.90	0.28
European Union - 27 countries	10.28	0.24
Finland	16.45	0.00
France	9.50	0.22
Germany	10.88	0.42
Greece	5.06	0.15
Hungary	5.73	0.22
Ireland	11.35	0.08
Italy	8.03	0.12
Latvia	7.10	0.15
Lithuania	9.60	0.28
Luxembourg	9.76	0.77
Malta	12.70	0.28
Montenegro	4.05	0.14
Netherlands	18.31	0.09
Norway	13.65	0.12

Slovakia's positioning is instructive as a representative case study of the broader CEE pattern. The country achieves sufficient enterprise-level digital intensity to qualify its firms in the very high digital intensity tier, yet these same enterprises demonstrate AI adoption rates that fall substantially below the EU central tendency. This divergence suggests that digital intensity classification, as currently operationalised in the Eurostat framework, captures technological infrastructure endowment but may not adequately reflect the full range of complementary assets — including AI-skilled human capital, data governance maturity, and access to AI development ecosystems — that translate infrastructure into adoption outcomes. The z-score of -0.759 places Slovakia's performance at a level consistent with structural barriers beyond mere technological readiness, pointing to the importance of institutional and investment dimensions in shaping national AI adoption trajectories that aggregate digital intensity metrics do not capture. Corrado et al. (2022) provide a relevant theoretical anchor here, demonstrating that economies lagging in intangible capital accumulation face structural barriers to frontier technology adoption that are not easily overcome by short-term investment initiatives — a dynamic that maps

directly onto the observed divergence between Slovakia's digital intensity classification and its AI adoption performance.

6. Discussion

6.1 Primary Finding Interpretation

The finding that the Spearman rank correlation between country-level mean AI adoption rates for very high digital intensity enterprises and very low digital intensity enterprises across 34 EU countries yields $\rho = -0.044$ ($p = 0.8048$) — a negligible and statistically non-significant association — indicates that no detectable moderate-to-large cross-tier co-movement in AI adoption is observable at the aggregate national level. This finding is consistent with, but does not confirm, several competing interpretations: national contextual factors may not uniformly condition AI adoption across the enterprise digital intensity spectrum; firm-level digital maturity may condition AI adoption outcomes differentially across tiers; or the present analytical design may lack the statistical power or resolution to detect an underlying pattern if one exists. The confidence interval around $\rho = -0.044$, which spans approximately $[-0.38, +0.30]$, is equally compatible with no relationship, moderate positive co-movement, and moderate negative co-movement. The power constraints outlined in Section 4.2 require that no single interpretation be selected as the preferred conclusion on the basis of this evidence alone.

This finding has potential implications for the TOE framework (Tornatzky and Fleischer, 1990): if national contextual factors were the dominant driver of AI adoption, one would expect strong positive co-movement across intensity tiers, as the environmental dimension of TOE would exert uniform pressure on all firms regardless of their technological context. The absence of detectable co-movement is consistent with the interpretation that the technological context dimension plays a differentiating role across digital intensity tiers, but this interpretation cannot be established from the correlation evidence alone given the wide confidence interval and the power limitations of the $n = 34$ design. Larger-sample analyses, or analyses exploiting within-country variation, would be required to adjudicate among competing theoretical explanations.

A further analytical consideration concerns the aggregation process itself. Averaging across heterogeneous annual observations — particularly given that AI adoption data were unavailable for earlier survey waves in many countries, and that the technology's diffusion trajectory means that recent years contain systematically higher adoption values — may suppress country-level signals that would be more apparent in a properly specified panel model. This constitutes an ecological fallacy risk in the methodological sense described by aggregation bias literature: the absence of a detectable aggregate cross-tier association does not preclude the existence of within-country, within-year relationships that disaggregated analysis would reveal. The cross-tier null result at the country-mean level thus speaks to the macro-aggregate analytical level and cannot be straightforwardly translated to firm-level or within-year inferences.

6.2 Literature Comparison

These results extend and partially refine prior findings in ways that deepen the theoretical understanding of the digital intensity--AI adoption nexus. The non-significant aggregate co-movement result is consistent with Cirillo et al. (2023), who find that digital investment levels are positively associated with advanced technology adoption at the firm level — a firm-level finding that does not necessitate cross-tier co-movement at the national level and is therefore not contradicted by the present results. The appropriate interpretation is that firm-level digital maturity may differentiate adoption outcomes within countries, but this differentiating effect does not manifest as a detectable positive correlation between the adoption rates of the most and least digitally mature enterprise tiers when aggregated across heterogeneous national contexts. The results are consistent with Dahlke et al. (2023), whose epidemic diffusion framework predicts that aggregate co-movement between digital intensity tiers should increase as AI adoption matures and inter-firm spillovers deepen; the present evidence is consistent with the interpretation that AI diffusion processes in many EU countries have not yet advanced sufficiently for national context effects to generate detectably uniform cross-tier adoption patterns. Faiz

et al. (2024) explicitly caution that no single indicator — including digital infrastructure — constitutes a sufficient predictor of technology adoption outcomes in enterprise settings, and the present null result reinforces this caution at the aggregate cross-national level. Taken together, these comparisons indicate that the present results do not negate firm-level findings but rather expose the boundary conditions at which those findings do not scale straightforwardly to cross-national aggregate analysis.

6.3 Policy and Managerial Implications

From a policy perspective, the absence of detectable positive cross-tier co-movement in AI adoption at the country level carries important implications for how EU digital and AI policy is designed and targeted. The finding is consistent with the interpretation that national-level structural factors do not uniformly elevate AI adoption across all enterprise digital intensity tiers, though alternative explanations — including analytical limitations of the current design — cannot be excluded. Irrespective of which interpretation ultimately prevails, the evidence suggests that broad national digitisation campaigns — which raise average digital intensity without necessarily addressing the specific complementary assets required for AI implementation — may be insufficient to drive population-level AI uptake. For bottom-quartile countries such as Slovakia — where very high digital intensity enterprises demonstrate AI adoption rates substantially below the EU mean (mean = 5.69%, rank = 27/34, z-score = -0.759) — policy interventions should be designed to address the specific binding constraints that prevent digitally advanced enterprises from realising AI adoption. These constraints likely include ICT skills shortages, financing limitations for SME AI projects, and regulatory uncertainty around data use.

A more differentiated policy architecture — one that moves from broad digitisation support toward targeted AI readiness auditing at the national level, including explicit assessment of intangible capital endowments as identified by Corrado et al. (2022) — would better align resource allocation with observed adoption gaps across the EU. Policymakers should be cautious about using aggregate digital intensity indices as proxies for AI readiness without supplementary evidence on the complementary assets, skills infrastructure, and institutional supports that are required to convert digital infrastructure endowments into actual AI adoption outcomes.

For enterprise managers, the distributional evidence carries a direct strategic lesson: occupying the very high digital intensity tier does not automatically position an organisation for AI adoption, and firms that assume digital infrastructure investment automatically confers AI readiness may systematically underinvest in the complementary organisational assets that mediate the transition from digital maturity to AI implementation. This is evident from the CEE country pattern, where national enterprise populations achieving the highest digital intensity classification nonetheless exhibit AI adoption rates substantially below the EU average. Managers should conduct explicit AI readiness audits that separately assess data governance maturity, AI-skilled workforce availability, use-case feasibility, and change management capacity — moving beyond the infrastructure endowments captured by digital intensity indices to address the full complement of organisational resources that condition AI adoption success. The evidence from Gupta et al. (2020) reinforces this implication: digital analytics capability, which underpins meaningful AI implementation, depends not only on infrastructure investment but on accumulated data management maturity and analytical skill — assets that are distinct from the connectivity and e-commerce metrics that dominate Eurostat's digital intensity composite.

7. Conclusion

This study examined whether AI adoption rates among enterprises with very high digital intensity co-move with AI adoption rates among enterprises with very low digital intensity at the country level across 34 European countries, using Eurostat indicators drawn from the Community Survey on ICT Usage and E-Commerce in Enterprises. This cross-tier co-movement test was designed to probe whether national contextual factors condition AI adoption uniformly across the enterprise digital intensity spectrum or whether adoption trajectories are differentiated by firm-level digital maturity in ways that resist aggregation to national-level co-movement patterns.

The empirical findings are unambiguous within the power constraints of the analytical design: neither the Spearman rank correlation nor the supplementary Pearson correlation provides statistically significant evidence of positive cross-tier co-movement at the country level, with both coefficients falling in the negligible range by conventional standards. The distribution of AI adoption rates across the 331 country-year observations is substantially right-skewed — with a median of 4.95% against a mean of 9.42% — confirming that high adoption is concentrated in a small number of leading countries while the majority of EU nations cluster at lower adoption levels. With $n = 34$ country-level observations, the study has power to detect associations of approximately $|\rho| \geq 0.34$; the null result therefore indicates the absence of a detectable moderate-to-large cross-tier co-movement signal, while leaving open the possibility of weaker associations, or associations detectable only at finer analytical resolution, that the present design cannot resolve.

This paper contributes to the empirical literature by providing the first systematic cross-national test of cross-tier AI adoption co-movement using Eurostat panel data across 34 EU countries, demonstrating that aggregate AI adoption rates among the most and least digitally mature enterprise tiers do not exhibit detectable positive co-movement at the country level. This finding is consistent with — though does not establish — the interpretation that firm-level digital maturity plays a differentiating role in AI adoption outcomes across countries. The result challenges simplified narratives in which national digital transformation programmes are expected to lift AI adoption uniformly across the enterprise population, and reinforces the importance of attending to firm-level digital maturity as a potentially differentiating factor. By directly testing a hypothesis concerning national context effects against harmonised multi-country data — and by carefully delineating the analytical boundaries of what this test can and cannot establish — the study contributes an empirical corrective to theoretical frameworks that had not previously been subjected to this level of cross-national scrutiny at the aggregate level.

Three directions for future research are indicated. First, future research should disaggregate the analysis by enterprise size class and sector to determine whether cross-tier co-movement patterns differ systematically within specific firm categories where national context effects may operate more uniformly. Second, longitudinal panel models incorporating country-level institutional variables — such as AI regulatory frameworks, public R&D investment, digital skills indices, and intangible capital endowments — should be developed to identify the moderating conditions under which national context effects do produce uniform cross-tier adoption patterns; such models should exploit the full $n = 331$ temporal panel rather than collapsing to country means, and should account for the differential number of observations contributing to national estimates. Third, qualitative comparative case studies contrasting top-quartile AI-adopting countries with bottom-quartile counterparts of similar digital intensity scores — following the logic suggested by Slovakia's positioning — would illuminate the causal mechanisms and contextual configurations that aggregate correlation analysis cannot capture. This study contributes to the growing body of evidence on the limits of single-indicator and aggregate approaches to technology adoption prediction and the importance of multi-dimensional, context-sensitive frameworks for understanding AI diffusion across European enterprise ecosystems.

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AI Adoption for ICT Security vs. Marketing: A Cross-Functional Application Analysis

Nora Grisáková¹ and Slavka Šagátová²

¹ Bratislava University of Economics and Business, Faculty of Business Management, Dolnozemska cesta 1, 852 35 Bratislava, Slovakia (EU); e-mail: nora.grisakova@euba.sk

² Bratislava University of Economics and Business, Faculty of Business Management, Dolnozemska cesta 1, 852 35 Bratislava, Slovakia (EU); e-mail: slavka.sagatova@euba.sk

Abstract

This study examines the adoption of artificial intelligence (AI) across European countries. It focuses on cross-functional applications in ICT security and marketing and sales. The empirical analysis is based on a harmonized Eurostat dataset covering 34 countries over the period 2021–2025. The dataset comprises 368 country–year observations. The methodological approach combines descriptive statistics with correlation analysis. Both Spearman and Pearson coefficients are used to assess the strength and stability of relationships between the analysed indicators. The results reveal a strong and statistically significant association between AI adoption in the two domains. This indicates consistent cross-country alignment. At the same time, substantial heterogeneity persists. This is reflected in high dispersion and right-skewed distributions. These findings suggest that AI adoption is not domain-specific. Instead, it reflects broader structural conditions related to digital and organisational capabilities. The study contributes to the literature by providing a distribution-sensitive perspective on AI adoption. It also highlights the importance of systemic factors in shaping cross-functional implementation patterns.

1. Introduction

The increasing diffusion of artificial intelligence (AI) technologies represents a fundamental dimension of digital transformation. It has significant implications for organisational processes and cross-functional integration within firms. In the European Union, AI adoption exhibits substantial cross-country heterogeneity. This reflects differences in technological infrastructure, organisational capabilities, and institutional environments. Existing empirical research has predominantly relied on aggregated indicators and mean-based comparisons. These approaches tend to obscure variability, dispersion, and structural asymmetry in adoption patterns. As a result, current approaches provide only a partial understanding of how AI adoption manifests across functional domains. This limitation is particularly relevant in the context of cross-functional implementation. In such contexts, adoption patterns appear to reflect systemic rather than domain-specific dynamics.

In response to this research gap, the present study examines the relationship between AI adoption in ICT security and marketing and sales across European countries. It places explicit emphasis on distributional characteristics and structural alignment. The study applies a distribution-sensitive methodological approach based on harmonised Eurostat data. It combines descriptive statistical analysis with correlation techniques to capture both variability and interdependence between the analysed indicators. This design enables a structured assessment of adoption patterns. It does not rely on causal assumptions. The contribution of the study lies in advancing a more nuanced empirical perspective on AI adoption.

2. Theoretical Background

The adoption of artificial intelligence (AI) in organizations can be conceptualized as a systemic process. This process is shaped by the interaction of structural conditions, organizational capabilities, and dynamic learning mechanisms. Rather than representing isolated technological decisions, AI adoption reflects the alignment of multiple determinants. These determinants operate across technological,

organizational, and environmental dimensions. To capture this complexity, the present study integrates the Technology–Organization–Environment (TOE) framework with capability-based perspectives, diffusion processes, and complementarity theory. This integrative approach provides a conceptual basis for explaining the co-occurrence of AI adoption across functional domains. These domains include ICT security (PITS) and marketing and sales (PMS). At the same time, the framework enables the interpretation of cross-country variability as an outcome of uneven structural and capability conditions. It therefore focuses on explanatory alignment rather than causal inference, consistent with the design of the study.

The TOE framework serves as the structural anchor. It identifies the contextual conditions that shape technology adoption (Tornatzky & Fleischer, 1990). In the context of AI, these conditions operate across multiple functional domains. Technological readiness, organizational resources, and environmental pressures influence adoption decisions in a systemic manner. This provides a theoretical basis for expecting alignment between PITS and PMS, as both indicators are influenced by shared underlying determinants. However, TOE primarily explains the presence of adoption. It does not explain its intensity or distribution across contexts. As a result, the framework captures structural preconditions but does not fully account for cross-country variability. This limitation highlights the need to incorporate perspectives that address differences in capability deployment and utilization.

Capability-based perspectives extend this structural view. They focus on how organizations translate contextual conditions into observable adoption outcomes. The resource-based view (Barney, 1991) and absorptive capacity theory (Cohen & Levinthal, 1990) emphasize the role of internal capabilities. AI adoption depends on the ability to integrate and exploit technological resources. In this context, indicators such as PITS and PMS can be interpreted as manifestations of underlying digital and organizational capabilities. This perspective implies that cross-functional adoption reflects shared capability structures rather than independent decision processes. At the same time, differences in capability levels contribute to variation in adoption intensity across countries. The framework therefore explains both alignment and variability as outcomes of uneven capability distribution.

Diffusion processes introduce a dynamic dimension. They account for the temporal expansion of technology use across organizational functions (Rogers, 2003). As organizations accumulate experience and reduce uncertainty, AI adoption may extend from initial applications to broader functional areas. This mechanism provides a theoretical basis for the observed association between PITS and PMS. However, diffusion alone does not explain the persistence of alignment across heterogeneous national contexts. The consistency of adoption patterns despite structural differences suggests interaction effects. Diffusion interacts with underlying capabilities and contextual conditions. This highlights the need to interpret diffusion as part of a broader systemic process. It should not be treated as a standalone explanatory mechanism.

Complementarity theory further integrates these perspectives. It emphasizes the interdependence of organizational investments (Milgrom & Roberts, 1995). In the context of AI, shared data infrastructures, analytical tools, and organizational processes create enabling conditions. Under these conditions, adoption in one domain increases the returns of adoption in another. This provides a direct explanation for the co-occurrence of AI deployment across functional areas. At the same time, complementarities imply that adoption patterns may reinforce existing differences. They may not necessarily reduce them. The concept of AI as a general-purpose technology strengthens this interpretation. Its value depends on coordinated investments across organizational functions (Brynjolfsson et al., 2019). This perspective aligns with the simultaneous presence of alignment and heterogeneity observed in empirical patterns.

The integrated framework provides a coherent basis for linking structural conditions, capability differences, and dynamic processes to observable adoption patterns. The TOE framework explains shared contextual determinants. Capability-based perspectives account for differences in implementation. Diffusion captures temporal expansion, while complementarity explains cross-functional reinforcement. Together, these perspectives support the interpretation of AI adoption as a systemic phenomenon. This phenomenon is characterized by both alignment and variability. This conceptual integration directly informs the methodological design and the empirical analysis that follows. This ensures consistency between theoretical reasoning and observed data patterns.

3. Literature Review

The adoption of artificial intelligence (AI) has evolved into a multidimensional organizational phenomenon. Existing research highlights structural conditions, adoption dynamics, and firm-level capabilities. However, these dimensions are typically analysed in isolation. As a result, the literature provides a fragmented understanding of cross-functional AI adoption. This limitation is particularly relevant in systemic implementation contexts. In such cases, adoption reflects structural rather than domain-specific determinants. Recent studies further link AI adoption to broader digital transformation processes and Industry 4.0 dynamics (Bongomin et al., 2020; Yaqub & Alsabban, 2023). However, these studies rarely integrate multiple explanatory mechanisms. This restricts their ability to capture the complexity of cross-domain adoption patterns. The following review therefore critically synthesizes key theoretical approaches. It evaluates both their explanatory contributions and their limitations.

3.1 Structural and Process Perspectives on Technology Adoption

The literature on technology adoption has been strongly influenced by structural frameworks. The Technology–Organization–Environment (TOE) framework conceptualizes adoption as the outcome of interacting contextual factors (Tornatzky & Fleischer, 1990). Empirical studies confirm its relevance in digital transformation contexts (Nguyen et al., 2022). These studies demonstrate that technological readiness, organizational resources, and environmental pressures shape adoption decisions. However, TOE primarily captures antecedent conditions. It does not explain how adoption unfolds across multiple functional domains. As a result, the framework provides only a partial explanation of cross-functional alignment. It identifies necessary conditions but does not account for observed variability. This limitation becomes critical when analysing systemic adoption patterns.

Diffusion of innovations theory introduces a temporal dimension to adoption processes (Rogers, 2003). It conceptualizes adoption as a staged process driven by learning and uncertainty reduction. This perspective is useful for explaining differences in adoption timing. However, it focuses on progression rather than structural configuration. It does not explain why adoption levels across functions tend to align. Moreover, diffusion assumes gradual expansion. This assumption may not hold in environments with strong structural constraints. Consequently, diffusion and TOE offer complementary insights. However, they do not fully explain co-adoption patterns across domains. Their explanatory power remains limited when applied in isolation.

These limitations are amplified in the context of AI. AI technologies are increasingly standardized and widely accessible. Under such conditions, external factors alone cannot explain adoption differences. Empirical research also highlights the role of managerial attitudes and behavioural intentions (Cao et al., 2021). These factors introduce additional variability beyond structural determinants. However, they are often analysed separately from systemic conditions. This fragmentation limits explanatory coherence. It suggests the need for integrating structural and internal perspectives. Without such integration, cross-functional adoption patterns remain insufficiently explained.

3.2 Capability-based Perspectives and Organizational Transformation

Capability-based theories shift the focus to internal organizational resources. The resource-based view (RBV) explains performance differences through firm-specific capabilities (Barney, 1991). In the context of AI, this implies that technology availability is not decisive. Instead, adoption depends on the ability to integrate and exploit digital resources. Empirical studies conceptualize AI capability as a multidimensional construct (Mikalef & Gupta, 2021). This includes technological infrastructure, human capital, and organizational processes. These findings highlight the central role of capabilities in shaping adoption outcomes. However, RBV primarily explains variation in performance. It does not directly explain alignment across functional domains. This creates a conceptual gap between capability theory and observed cross-domain patterns.

The concept of absorptive capacity further refines this perspective (Cohen & Levinthal, 1990). It emphasizes the ability to recognize and utilize external knowledge. In AI adoption, this capability supports the transfer of knowledge across domains. Firms with higher absorptive capacity may extend AI usage more effectively. However, empirical evidence indicates that this process is not uniform.

Similar capability levels may result in different adoption outcomes. This suggests that additional factors influence capability deployment. Data-driven innovation processes reinforce this complexity (Sultana et al., 2021). They enable systematic transformation of data into insights. Yet, they do not guarantee consistent cross-functional implementation.

IT capability theory extends this argument by emphasizing integrated resource configurations (Bharadwaj, 2000). It highlights the need for coordinated investments across technological and organizational dimensions. Complementarity theory further strengthens this view (Milgrom & Roberts, 1995). It suggests that investments in one domain increase returns in others. However, these frameworks assume positive reinforcement effects. They do not fully account for situations where complementarities reinforce low adoption levels. As a result, capability-based perspectives explain heterogeneity. However, they do not fully explain consistent alignment across domains. This limitation indicates the need for a more integrative analytical framework.

3.3 Cross-functional AI Adoption and Systemic Integration

Recent research emphasizes the systemic nature of digital transformation. The concept of digital maturity links technological capabilities with organizational alignment (Westerman et al., 2014). Firms with higher digital maturity tend to implement technologies across multiple domains. This perspective provides a direct explanation for cross-functional adoption patterns. However, digital maturity is often measured using composite indicators. These indicators may obscure internal variability. As a result, the concept explains coordination but not dispersion. This limits its explanatory precision in cross-country analyses.

Empirical studies confirm that AI is deployed across multiple functional areas (Dwivedi et al., 2021; Capuano et al., 2022). This includes marketing, cybersecurity, and operations. These patterns suggest the presence of shared underlying capabilities. However, the strength of these relationships varies across contexts. This variability indicates that systemic integration is not uniform. AI deployment is also embedded in broader technological ecosystems (Bzai et al., 2022). These include IoT and interconnected digital infrastructures. While these systems enable integration, they also introduce complexity. This complexity may generate both alignment and divergence.

The concept of AI as a general-purpose technology provides an additional explanation (Brynjolfsson et al., 2019). It emphasizes complementarities and the need for coordinated investments. However, such investments may generate uneven outcomes. High-capability environments may benefit more than low-capability ones. This introduces structural divergence rather than convergence. Additional factors such as governance and risk management further influence adoption (Lobschat et al., 2021; Wong et al., 2022). These factors may constrain or enable cross-functional expansion. Despite these insights, empirical studies rarely examine distributional characteristics. Most rely on mean-based comparisons. This approach obscures variability and structural asymmetry. As a result, systemic adoption dynamics remain only partially understood.

3.4 Research Gap

Despite extensive research, several critical gaps remain. First, theoretical frameworks are rarely integrated into a unified model. TOE, diffusion, and RBV are typically applied separately. Their combined explanatory power remains underexplored. Second, empirical studies rely on binary or mean-based indicators. This limits the ability to capture variability and distributional asymmetry. Third, cross-functional adoption is not systematically analysed at the aggregate level. The relationship between domain alignment and structural conditions remains unclear. This gap is particularly relevant in the European context, where heterogeneity is pronounced.

The present study addresses these limitations through a distribution-sensitive approach. It integrates variability measures with correlation analysis. This enables a structured examination of cross-domain relationships. The analysis focuses on alignment and dispersion simultaneously. This approach provides a more nuanced understanding of AI adoption patterns. It also establishes a direct link between theoretical constructs and observable outcomes. This framework informs the methodological design presented in the following chapter.

4. Methodology

This chapter outlines the methodological framework used to examine the relationship between artificial intelligence (AI) adoption across functional domains within European enterprises. The approach directly responds to the research gap identified in the preceding sections, which emphasizes the limited consideration of variability, dispersion, and structural alignment in existing studies. The methodological design is therefore constructed to capture both distributional properties and relational patterns of AI adoption at the country level. The analysis relies on a secondary dataset derived from harmonized Eurostat indicators, ensuring cross-country comparability and methodological consistency. Particular attention is given to combining descriptive and inferential techniques in a coherent analytical sequence. This allows for a systematic assessment of variability, asymmetry, and interdependence between the analysed indicators.

4.1 Data Source and Panel Construction

The empirical analysis is based on secondary data obtained from the Eurostat Community Survey on ICT Usage and E-Commerce in Enterprises, specifically the dataset Artificial intelligence by size class of enterprise (isoc_eb_ai), accessed on 27 February 2026 (Eurostat, 2024). The reference period covers the years 2021 to 2025. Data are available for four survey waves: 2021, 2023, 2024, and 2025. The dataset includes 34 European countries, comprising EU Member States and associated economies. It represents a harmonized statistical source based on standardized definitions and stratified sampling procedures. This ensures a high level of comparability across countries and over time.

The analysis focuses on two indicators representing complementary dimensions of AI adoption. The first indicator, ICT security E_AI_PITS (PITS) (EUROSTAT, 2026a), measures the proportion of enterprises using AI technologies for ICT security protection. The second indicator, AI adoption in marketing and sales E_AI_PMS (PMS) (EUROSTAT, 2026b), captures the proportion of enterprises applying AI in marketing and sales functions. Both indicators are expressed as percentages of firms reporting use of AI, weighted by firm size categories. They therefore represent aggregated measures of adoption at the national level. In line with the theoretical framework, these variables serve as proxies for broader digital and organizational capabilities. PITS reflects security-oriented technological deployment, while PMS captures customer-facing and market-oriented applications.

After merging all available observations, the resulting country–year–firms of different size categories panel contains 368 observations. This full panel forms the basis for descriptive and distributional analysis. In addition, country-level aggregation is applied to construct a second dataset of 34 mean values for each indicator. These aggregated values represent the primary unit of analysis in the inferential stage. This approach ensures that the effective sample size corresponds to the number of countries rather than repeated observations. It also reduces the risk of inflated statistical significance caused by within-country autocorrelation.

4.2 Analytical Procedure

The analytical procedure consists of a sequence of structured steps designed to ensure both descriptive transparency and inferential robustness. The approach follows an exploratory-correlational design that is consistent with the study's objective of examining relationships between AI adoption dimensions across countries. Each step builds on the previous one and contributes to a coherent analytical framework.

In the first step, the full country–year panel ($n = 368$) is subjected to detailed descriptive statistical analysis. Measures of central tendency include the mean and median. Dispersion is assessed using standard deviation and the coefficient of variation. Additional distributional characteristics include minimum, maximum, quartiles, and interquartile range. The standard error of the mean and 95% confidence intervals are calculated to quantify statistical uncertainty. The distribution is further evaluated in terms of skewness, which informs the choice of subsequent analytical techniques. Visual inspection is supported by graphical tools, including boxplots stratified by survey year. This step directly addresses the research gap by incorporating variability and distributional asymmetry into the analysis.

In the second step, country-level mean values for PITS and PMS are calculated. These values are obtained by averaging observations across all available years within each country. The resulting dataset contains 34 country-level pairs. This aggregation enables cross-country comparison while maintaining analytical consistency. It also ensures that inference is based on independent observational units. However, the unbalanced panel implies that the precision of estimates varies across countries.

In the third step, a robustness-oriented analysis is conducted at the level of individual survey waves. The Spearman rank-order correlation coefficient is calculated separately for each available year. This allows assessment of temporal stability in the observed relationship. It also helps determine whether the overall association is driven by a specific cross-section. For each wave, the number of valid country observations and corresponding p-values are reported. This ensures transparency regarding statistical power and reliability.

In the fourth step, the primary inferential analysis is performed using the Spearman rank-order correlation coefficient (Spearman, 1904). This measure is applied to the 34 country-level mean pairs. The choice of Spearman's ρ reflects the observed right-skewness and limited sample size. Unlike parametric alternatives, it does not require normal distribution and is robust to outliers and monotonic non-linear relationships. For completeness, the Pearson correlation coefficient is also reported as a parametric reference. The choice of method is further supported by the Shapiro–Wilk test of normality. Prior to applying the correlation analysis, the distributional properties of the dataset were examined in order to assess the suitability of parametric and non-parametric methods. The dataset consists of both panel observations (country–year pairs) and aggregated country-level values derived as means across the observed period. The assessment of distributional characteristics included measures of skewness, dispersion, and variability. Normality was assessed at both panel and aggregated levels to account for potential differences in distributional properties resulting from data aggregation. The full panel dataset exhibits pronounced variability and right-skewness, while aggregation reduces distributional asymmetry but does not eliminate underlying heterogeneity. These differences were taken into account when selecting appropriate statistical techniques. Consequently, the Spearman rank-order correlation coefficient was used as the primary inferential measure, while the Pearson coefficient was retained for comparative purposes.

In the fifth step, country-level values are standardized using z-scores. This transformation enables direct comparison of relative positions within the overall distribution. It also facilitates the identification of deviations from the mean. The standardized values are used to interpret relative performance across countries. Particular attention is given to countries located in the lower and upper quartiles. Quartile classification provides an additional perspective on structural heterogeneity.

Finally, Slovakia is analysed as a focal case within the European distribution. Its position is evaluated using multiple complementary metrics. These include its mean value, rank position, z-score, and distance from the sample mean. This multi-dimensional approach enables a precise characterization of its relative standing. It also ensures consistency with the broader cross-country analysis and supports interpretation within the identified structural patterns.

5. Results

This chapter presents the empirical results of the analysis, focusing on the distributional characteristics and interrelationships of artificial intelligence (AI) adoption across European countries. The results are structured to reflect the sequential logic of the applied methodology, beginning with a detailed descriptive assessment of the country–year panel data, followed by inferential analysis at the level of country aggregates. Particular attention is given to the examination of central tendency, variability, and distributional asymmetry, which provide insight into the structural heterogeneity of AI adoption across functional domains. The analysis further evaluates the strength and stability of the relationship between the examined indicators using both non-parametric and parametric correlation measures. All findings are reported in a descriptive and statistically grounded manner, consistent with the exploratory-correlational design of the study and without extending into causal interpretation.

5.1 Descriptive Statistics

The descriptive analysis is based on a full panel dataset comprising 368 observations, covering AI adoption in ICT security E_AI_PITS (PITS) and marketing and sales E_AI_PMS (PMS). The mean value reaches 8.090% for PITS and 6.905% for PMS. Median values are lower. The standard deviation equals 9.253 for PITS and 6.364 for PMS. The coefficient of variation reaches 114.372% for PITS and 92.164% for PMS. The standard error of the mean is 0.482 for PITS and 0.332 for PMS, with corresponding 95% confidence intervals (table 1).

The range of values indicates substantial dispersion across observations. Minimum values are 0.000 for both PITS and PMS. Maximum values reach 54.580 for PITS and 35.760 for PMS. The interquartile range equals 9.640 for PITS and 6.900 for PMS (table 1). These statistics indicate a wide spread within the central portion of the distribution.

Table 1. Descriptive Statistics

Statistic	Value for PITS	Value for PMS
n	368	368
mean	8.090	6.905
median	4.250	4.780
standard error	9.253	6.364
sem	0.482	0.332
CI95_low	7.142	6.252
CI95_high	9.039	7.557
min	0.000	0.000
max	54.580	35.760
Q1	1.750	2.283
Q3	11.390	9.183
IQR	9.640	6.900
CV_%	114.372	92.164

The distributional shape is characterized by positive skewness in both variables. The skewness coefficient reaches 1.982 for PITS and 1.491 for PMS. These values indicate right-skewed distributions with extended upper tails. The difference between mean and median values is observable in both indicators. This difference is larger for PITS than for PMS. The distributional asymmetry is therefore more pronounced in the PITS variable.

5.2 Correlation Results

The correlation analysis is based on 34 country-level aggregate observations derived from mean values across the observed period. The mean value of PITS equals 7.686, while the mean value of PMS equals 6.576. The standard deviation reaches 4.785 for PITS and 3.277 for PMS, corresponding to coefficients of variation of 62.258% and 49.833%, respectively. Median values equal 7.204 for PITS and 6.142 for PMS, while the interquartile ranges reach 5.320 and 4.369. Minimum and maximum values range from 0.220 to 21.239 for PITS and from 1.720 to 14.810 for PMS, indicating substantial cross-country dispersion in both indicators.

The distribution of aggregated values exhibits moderate positive skewness. The skewness coefficient reaches 0.775 for PITS and 0.508 for PMS. Quartile thresholds further indicate variability across countries, with Q1 equal to 4.379 and Q3 equal to 9.699 for PITS, and Q1 equal to 3.904 and Q3 equal to 8.273 for PMS. The standard error of the mean equals 0.821 for PITS and 0.562 for PMS, reflecting the sampling variability of aggregated observations.

The normality of the aggregated distributions was assessed using the Shapiro–Wilk test. For PITS, the test statistic reaches $W = 0.95$, indicating that the distribution does not exhibit strong deviation from

normality at the aggregated level. However, this result contrasts with the distributional properties observed in the full panel dataset ($n = 368$), where pronounced right-skewness and high dispersion are present. The persistence of distributional asymmetry at the panel level suggests that aggregation reduces, but does not fully eliminate, underlying heterogeneity.

The correlation analysis indicates a strong and statistically significant association between the two indicators. The Spearman rank-order correlation coefficient reaches $\rho = 0.909$. The Pearson correlation coefficient reaches $r = 0.841$. The corresponding t-statistic equals 12.336, with a p-value of 1.05474×10^{-13} . These values confirm a statistically significant relationship based on 34 country-level observations.

An additional correlation analysis based on the full panel dataset ($n = 368$) yields consistent results. The Pearson correlation coefficient reaches $r = 0.872$, while the Spearman coefficient reaches $\rho = 0.866$. The corresponding t-statistic equals 33.103, with a p-value of 4.2139×10^{-112} . These results confirm the stability of the association across different levels of data aggregation.

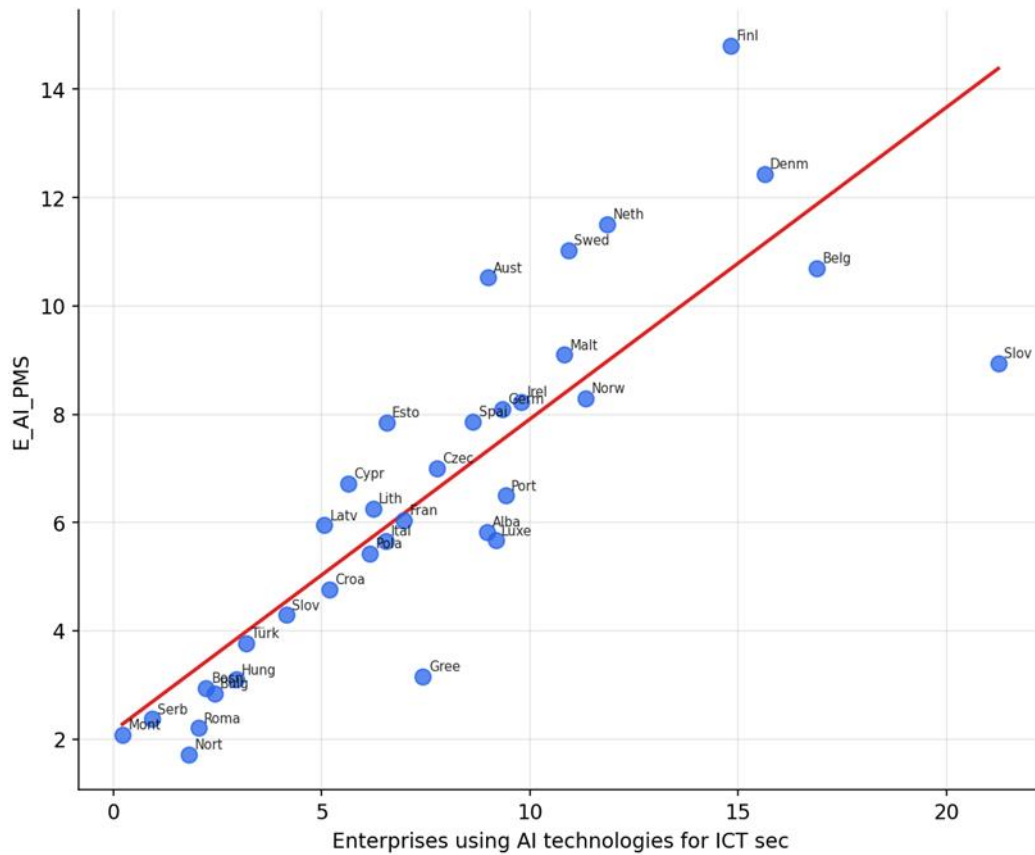


Figure 1. Scatter: Enterprises using AI PITS vs. PMS ($n=34$)

Source: own processing accordint to Eurostat (EUOSTAT, 2026a; EUROSTAT, 2026b)

Table 2. Percentage of enterprises using AI technologies - Correlation Data

Country	PITS (%)	PMS (%)
Albania	8.97	5.83
Austria	8.99	10.52
Belgium	16.89	10.69
Bosnia and Herzegovina	2.23	2.94
Bulgaria	2.43	2.85
Croatia	5.18	4.76

Cyprus	5.64	6.72
Czechia	7.77	7.00
Denmark	15.63	12.44
Estonia	6.56	7.84
Finland	14.83	14.81
France	6.97	6.03
Germany	9.33	8.09
Greece	7.43	3.15
Hungary	2.95	3.10
Ireland	9.79	8.22
Italy	6.54	5.66
Latvia	5.07	5.95
Lithuania	6.24	6.25
Luxembourg	9.18	5.67
Malta	10.83	9.10
Montenegro	0.22	2.08
Netherlands	11.85	11.51
North Macedonia	1.81	1.72
Norway	11.34	8.29
Poland	6.16	5.43
Portugal	9.42	6.50
Romania	2.04	2.20
Serbia	0.92	2.37
Slovakia	4.15	4.29
Slovenia	21.24	8.94
Spain	8.64	7.86
Sweden	10.93	11.02
Türkiye	3.18	3.77

own processing accordint to Eurostat (EUOSTAT, 2026a; EUROSTAT, 2026b)

5.3 Country-Level Patterns and Slovakia Context

Country-level values of PITS exhibit substantial dispersion across the 34 observed countries. The mean value reaches 7.686, with a standard deviation of 4.785 and a coefficient of variation of 62.258%. The minimum value equals 0.220 (Montenegro), while the maximum reaches 21.239 (Slovenia), indicating a range exceeding 21 percentage points. Median values reach 7.204, while quartile thresholds are defined by $Q1 = 4.379$ and $Q3 = 9.699$, with an interquartile range of 5.320. These distributional characteristics indicate a wide spread of values across countries despite the aggregation of observations. The dispersion remains evident when comparing absolute values as well as relative positioning within the distribution. The observed variability is consistent with the distributional properties identified at the panel level, where higher dispersion and skewness are more pronounced.

The standardized distribution further illustrates differences in relative country positioning. Z-scores range from -1.560 (Montenegro) to 2.832 (Slovenia), reflecting the distance of individual country values from the cross-country mean. Slovakia reaches a z-score of -0.739 , indicating a below-average position within the distribution. Positive z-scores are concentrated among countries in the upper quartile, including Slovenia, Belgium, Denmark, and Finland. Negative values are predominantly observed among countries in the lower quartile, including Montenegro, Serbia, and North Macedonia. The distribution of z-scores shows a concentration around the mean with a gradual extension toward

higher values. This pattern is consistent with moderate skewness observed in the aggregated dataset (skewness = 0.775).

The ranking of countries based on PITS confirms the heterogeneity of adoption levels. Slovenia occupies the first position, followed by Belgium (16.89) and Denmark (15.63), while Montenegro, Serbia, and North Macedonia occupy the lowest positions. Slovakia ranks 26th out of 34 countries with a value of 4.15. The difference between Slovakia and the cross-country mean equals 3.536 percentage points, corresponding to approximately 46.0% below the mean value. Slovakia's position falls below the first quartile threshold, placing it within the lower quartile of the distribution. The relative positioning is consistent across both absolute values and standardized measures. The distribution of country-level values indicates that lower-ranked countries are clustered within a relatively narrow range compared to the upper tail.

The relationship between PITS and PMS at the country level is illustrated by the scatter plot (Figure 1), which includes 34 aggregated observations. Data points are distributed along a diagonal pattern, reflecting the strong monotonic association identified in the correlation analysis (Spearman $\rho = 0.909$). The alignment between variables is observable across the entire range of values, with no extreme deviations from the general pattern. The dispersion of points around the diagonal reflects variability in absolute values rather than structural breaks in the relationship. The visual distribution is consistent with the statistical results reported in Section 5.2.

The boxplot representation (Figure 2) illustrates the distribution of PITS values across countries and observation periods. The box represents the interquartile range, while whiskers extend to $1.5 \times \text{IQR}$. The presence of outliers is observable in the upper range of the distribution, corresponding to countries with high adoption levels. The spread of values varies across observation periods, reflecting differences in dispersion within the dataset. Aggregation reduces the extent of extreme values but does not eliminate variability across countries. The graphical representation confirms the presence of heterogeneity observed in descriptive statistics.

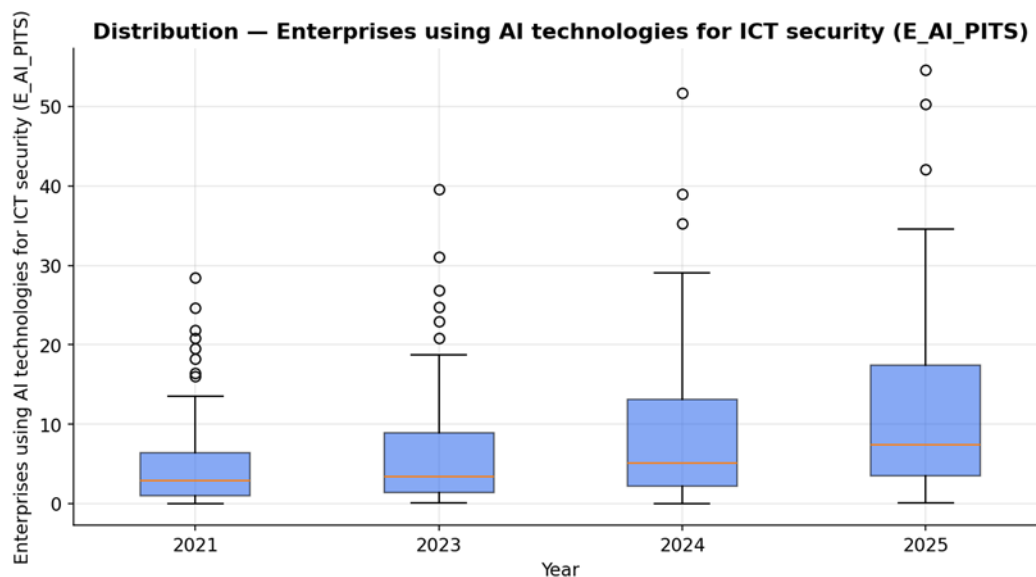


Figure 2. Boxplot of Enterprises using AI technologies for ICT security (PITS) across EU countries per year. Box=IQR, whiskers= $1.5 \times \text{IQR}$, dots=outliers.

Source: own processing according to Eurostat (EUOSTAT, 2026a; EUROSTAT, 2026b)

Overall, the country-level distribution is characterized by moderate skewness, substantial dispersion, and clear differentiation across quartiles. The aggregation of panel data reduces distributional asymmetry but retains variability in relative positioning. The results demonstrate consistent patterns across descriptive, standardized, and graphical representations. These findings provide a comprehensive characterization of cross-country differences in AI adoption levels within the observed dataset.

6. Discussion

This chapter provides a theoretical interpretation of the empirical patterns presented in the preceding section. The discussion focuses on explaining the observed patterns of association and variability. Particular emphasis is placed on the structural alignment between functional domains and the persistent cross-country heterogeneity identified in the data. Building on the exploratory-correlational design of the study, the analysis refrains from causal inference. Instead, it concentrates on theoretically grounded interpretation of statistically observed relationships. The findings are examined in relation to the Technology–Organisation–Environment framework and complementary capability-based perspectives. These perspectives provide an explanatory basis for the systemic nature of AI adoption.

6.1 *Synthesis of Empirical Patterns*

The empirical results indicate a strong association between AI adoption in ICT security and marketing and sales across countries. However, this association should not be interpreted as evidence of uniform adoption dynamics. The observed patterns simultaneously exhibit alignment and substantial dispersion. This is reflected in high coefficients of variation and quartile differences. While aggregation reduces distributional asymmetry, variability persists across countries. This persistence indicates structural heterogeneity. The coexistence of alignment and dispersion introduces ambiguity in interpretation. On one hand, it suggests coordinated development across domains. On the other hand, it may reflect shared constraints that limit adoption simultaneously. The empirical patterns therefore support multiple interpretations rather than a single explanatory framework.

An alternative interpretation considers that the observed alignment may not be driven by active coordination. Instead, it may result from common structural conditions. Countries with limited digital capacity may exhibit low adoption across all domains, while advanced countries display high adoption in parallel. This pattern suggests that alignment may emerge from constraints rather than complementarities. The presence of moderate skewness and high dispersion indicates that the distribution is influenced by a subset of high-performing countries. This concentration suggests that the observed relationship may be partially driven by upper-tail effects. The findings therefore highlight the need to interpret correlation patterns with caution. The empirical structure reflects both alignment and stratification.

6.2 *TOE Framework and Systemic Adoption Mechanisms*

Within the TOE framework, the observed alignment can be interpreted as the result of shared technological, organizational, and environmental conditions (Tornatzky & Fleischer, 1990). Countries with more developed infrastructures and institutional support tend to achieve higher adoption across domains. However, the empirical results also reveal variability that is not fully explained by TOE factors. Similar structural conditions do not always lead to comparable adoption levels. This suggests that TOE captures necessary conditions for adoption. However, these conditions are not sufficient to explain observed differences. The framework explains the presence of alignment. It does not explain the degree of dispersion observed across countries.

An alternative perspective emphasizes that TOE variables may operate differently depending on context. Organizational readiness or technological infrastructure may have varying effects across countries due to institutional or economic differences. This introduces tension between a systemic explanation and context-specific dynamics. The persistence of variability after aggregation further supports this view. While TOE predicts alignment, it does not predict the magnitude of differences between countries. Empirical extensions of the framework acknowledge these limitations (Nguyen et al., 2022). The results therefore indicate that TOE provides a partial explanation that requires supplementation by other theoretical perspectives.

6.3 *Interpretation Based on Capabilities, Complementarity and Heterogeneity*

From the perspective of the resource-based view, AI adoption reflects the deployment of internal capabilities rather than external conditions alone (Barney, 1991). The observed alignment between domains may indicate that shared capabilities enable firms to implement AI across multiple functions.

However, the high variability in adoption levels suggests that these capabilities are unevenly distributed. This introduces a potential tension within the RBV framework. While the framework explains differences in performance, it does not fully account for cross-country variation in adoption outcomes. Similar capability levels may still result in different adoption patterns. The concept of absorptive capacity further refines this interpretation by focusing on knowledge acquisition and application (Cohen & Levinthal, 1990). Firms with higher absorptive capacity may extend AI usage across domains more effectively. Nevertheless, the empirical data indicate that this process is not uniform. Variability persists even among countries with comparable adoption levels in one domain. This suggests that capability transfer across functions may be constrained. These constraints may be organizational or strategic in nature. Empirical research highlights the multidimensional nature of AI capability (Mikalef & Gupta, 2021). The findings therefore support a capability-based explanation but also reveal its limitations in explaining cross-country heterogeneity.

Complementarity theory suggests that investments in related capabilities reinforce each other. This reinforcement leads to coordinated adoption across domains (Milgrom & Roberts, 1995). The observed alignment between ICT security and marketing AI is consistent with this perspective. Shared data infrastructures and analytical tools may enable simultaneous adoption. This can occur without the need for separate investments. However, the empirical results also indicate that complementarities may operate differently across contexts. In countries with limited capabilities, complementarities may reinforce low adoption levels. In more advanced environments, they may amplify high adoption. This dual effect introduces an inherent tension within the complementarity framework. While the framework explains alignment, it may also contribute to divergence rather than convergence. The presence of high dispersion and skewness supports this interpretation. Complementarities may therefore amplify existing structural differences. They may not necessarily reduce them. AI as a general-purpose technology further reinforces this dynamic. It requires complementary investments to generate value (Brynjolfsson et al., 2019). At the same time, integration with broader technological systems may influence adoption patterns. This includes systems such as IoT infrastructures (Bzai et al., 2022). The findings highlight both the explanatory relevance and the limitations of complementarity-based interpretations.

The empirical results demonstrate substantial heterogeneity across countries. This heterogeneity remains observable even after aggregation. The coefficient of variation and quartile distribution indicate that adoption levels are unevenly distributed. Aggregation reduces distributional asymmetry. However, it does not eliminate variability in relative positioning. This suggests that structural differences persist across countries. These differences remain despite similar patterns of alignment. The distinction between alignment and convergence is therefore critical. The data indicate consistent relative ordering. However, they do not show a reduction in dispersion. An alternative interpretation considers that heterogeneity may reflect differences in measurement. It may not fully reflect underlying processes. Countries contribute unequal numbers of observations. This may influence aggregated values. This introduces potential bias in cross-country comparisons. At the same time, variability persists across multiple indicators. This suggests that the observed patterns are not purely statistical artefacts. The empirical structure reflects both genuine differences and methodological constraints. This dual interpretation highlights the importance of cautious inference. The findings therefore emphasize the need to consider both structural and methodological sources of heterogeneity.

6.4 Implications for Policy and Managerial Practice

The empirical findings suggest that policy interventions should focus on underlying capability structures. These interventions should not target isolated domains of AI adoption. The observed alignment indicates that adoption patterns are interconnected. However, substantial variability is present in the data. This suggests that uniform policy approaches may be ineffective. Countries differ not only in adoption levels but also in structural conditions. This requires differentiated strategies. These strategies should reflect local constraints and capacities. Policies aimed at improving digital infrastructure and skills may have broader effects. These effects may extend across multiple domains.

From a managerial perspective, the results highlight the importance of coordinated capability development. Cross-functional adoption may depend on shared resources. It may also depend on organizational integration. At the same time, variability in the data indicates that such coordination is

not uniformly achieved. Managers must address internal barriers. These barriers may limit the transfer of capabilities across domains. Governance and risk considerations may also influence adoption decisions (Wong et al., 2022; Lobschat et al., 2021). These factors introduce additional complexity into the adoption process. The implications therefore extend beyond technological investment. They also include organizational and strategic alignment.

7. Conclusion

7.1 Synthesis of Findings and Theoretical Implications

This study examined cross-country patterns of artificial intelligence adoption in ICT security (PITS) and marketing and sales (PMS) across European economies. The analysis combined panel and aggregated data. The results reveal a strong and statistically significant association between the two domains. This relationship remains consistent across different levels of data aggregation. At the same time, the analysis identifies substantial variability in adoption levels. This variability is reflected in dispersion measures and quartile distributions. The combination of alignment and heterogeneity suggests that countries maintain consistent relative positioning across domains. However, they differ markedly in absolute adoption intensity. The findings support the relevance of established theoretical perspectives, including the Technology–Organization–Environment framework, the resource-based view, and complementarity theory. However, none of these approaches fully explains the observed patterns in isolation. The results further show that aggregation reduces distributional asymmetry. At the same time, it does not eliminate underlying heterogeneity. This underscores the importance of distinguishing between panel-level and country-level properties. From a practical perspective, the findings point to the need for coordinated capability development. They also highlight the importance of context-sensitive policy interventions rather than domain-specific approaches to AI adoption. The study is subject to several limitations. These include data aggregation, cross-sectional structure, and the absence of firm-level analysis. These factors constrain causal interpretation. Future research should extend the analysis using longitudinal and micro-level data. This would enable a better understanding of the dynamics and determinants of AI adoption across organizational and institutional contexts.

7.2 Limitations and Future Research Directions

The findings are subject to several limitations that affect their interpretation. First, the use of aggregated country-level data may obscure variation within countries. Sectoral and firm-level differences are not captured in the current analysis. Second, the aggregation process reduces distributional asymmetry. However, it may also mask extreme values present in the panel dataset. This creates differences between panel-level and aggregated distributions. These differences must be explicitly considered. Third, the cross-sectional nature of the data limits the ability to analyze temporal dynamics. Future research could address these limitations by incorporating longitudinal and firm-level data. This would enable a more detailed analysis of adoption processes and variability. Additionally, further research may examine the interaction between AI adoption and other technological systems. The role of institutional and economic factors could also be explored in greater detail. These directions would contribute to a more comprehensive understanding of AI adoption patterns. The findings of the present study provide a basis for such extensions. At the same time, they highlight the complexity of the phenomenon.

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Ethical and Legal Barriers to AI Adoption: Prevalence and Policy Relevance Across the EU

Andriana Baziuk¹ and Simona Kosztanko²

¹ Bratislava University of Economics and Business, Faculty of Business Management, Dolnozemska cesta 1, 852 35 Bratislava, Slovakia (EU); e-mail: andriana.baziuk@euba.sk

² Bratislava University of Economics and Business, Faculty of Business Management, Dolnozemska cesta 1, 852 35 Bratislava, Slovakia (EU); e-mail: simona.kosztanko@euba.sk

Abstract

Despite growing momentum behind AI adoption in Europe, the specific role of ethical concerns and legal uncertainty as enterprise-level barriers remains insufficiently understood, particularly in the context of the EU AI Act's evolving regulatory demands. This article examines the prevalence, co-occurrence, and cross-national distribution of ethical and legal barriers to AI adoption among enterprises across EU member states. Drawing on Eurostat's Community Survey on ICT Usage and E-Commerce in Enterprises, the study analyzes indicators E_AI_BEC and E_AI_BLEG at the country level. Results reveal that both barriers are consistently co-reported across member states, with a strong positive correlation indicating that countries where enterprises frequently cite ethical concerns also tend to report elevated levels of legal uncertainty. Considerable cross-national variation is observed, with certain member states recording notably higher combined barrier prevalence, suggesting that institutional and regulatory environments mediate enterprise-level AI reluctance beyond organizational capability constraints alone. The findings further indicate that ethical and legal barriers function as institutionally co-determined phenomena rather than independent obstacles. These results provide policymakers with a systematic empirical foundation for designing differentiated, country-sensitive interventions that address ethical and legal impediments to AI adoption as structurally interrelated challenges within the EU's digital transformation agenda.

1. Introduction

As the EU advances its regulatory framework for artificial intelligence through the AI Act, understanding why enterprises continue to refrain from adopting AI technologies remains a critical policy challenge. Artificial intelligence has moved from the periphery of organizational strategy to the center of digital transformation agendas across Europe, however adoption rates among enterprises remain uneven and, in many member states, persistently low (Dwivedi et al., 2019). The EU AI Act represents the most comprehensive binding regulatory framework for artificial intelligence enacted anywhere in the world, creating a novel institutional environment in which enterprises must navigate simultaneously the promise of AI-driven productivity gains and the demands of regulatory compliance. In this context, understanding what specifically inhibits enterprises from adopting AI — beyond general technological immaturity — has become an urgent question for both policymakers and scholars.

Despite growing research on AI barriers, systematic cross-national empirical evidence on the specific role of ethical concerns and legal uncertainty in suppressing enterprise-level AI adoption across EU member states remains scarce. Existing research has devoted considerable attention to organizational capability gaps, resource constraints, and technological readiness as inhibitors of AI uptake (Mikalef & Gupta, 2021; Cohen & Levinthal, 1990). Ethical and legal dimensions, while frequently discussed in normative and governance-oriented literature, have rarely been operationalized as distinct, measurable barriers at the enterprise level, and virtually never examined comparatively across the EU using official statistical sources. This absence of systematic empirical evidence leaves policymakers without an adequate evidential foundation for designing differentiated support interventions.

This article examines the prevalence of ethical and legal barriers to AI adoption among EU enterprises, quantifies their co-occurrence and correlation, and maps their cross-country distribution to inform

evidence-based policy. Specifically, the study draws on Eurostat's Community Survey on ICT Usage and E-Commerce in Enterprises to analyze the indicators E_AI_BEC (enterprises reporting ethical concerns as an AI adoption barrier) and E_AI_BLEG (enterprises reporting legal uncertainty as an AI adoption barrier) across EU member states. By combining descriptive distributional analysis with bivariate correlation testing at the country level, the study generates systematic quantitative cross-national evidence on the co-occurrence of these two barrier types as institutionally co-determined phenomena.

The remainder of this article is structured as follows: Section 2 presents the theoretical background, situating the study within the Technology-Organization-Environment framework, Diffusion of Innovations theory, and institutional pressure perspectives. Section 3 reviews the relevant literature across three thematic domains — AI adoption barriers and organizational readiness, AI ethics governance frameworks, and institutional environments and EU AI regulation. Section 4 describes the methodological approach, including data sources, analytical procedures, statistical tests employed, and key limitations. Section 5 presents the empirical results, including descriptive statistics, correlation findings, and country-level rankings. Section 6 discusses the findings in relation to existing theory and literature, and derives policy and managerial implications. Section 7 concludes by summarizing the main contributions and identifying directions for future research.

2. Theoretical Background

The adoption of artificial intelligence by enterprises is not a purely technical decision. It is shaped by a complex interplay of organizational capabilities, environmental pressures, and institutional conditions that collectively determine whether and how quickly firms integrate new technologies into their operations. Three theoretical frameworks are particularly relevant for understanding how ethical concerns and legal uncertainty function as barriers to AI adoption across EU member states.

The Technology-Organization-Environment (TOE) framework (Tornatzky, Fleischer, 1990), remains one of the most widely applied analytical lenses in technology adoption research. The framework suggests that an organization's decision to adopt a technology is influenced by three factors: the characteristics of the technology, the organization's internal attributes, and the external environment in which the organization operates. The environmental dimension encompasses industry structure, regulatory conditions, and broader societal norms — precisely the domain in which ethical governance and legal uncertainty about AI reside. When the regulatory environment is ambiguous or rapidly evolving, as is currently the case with the EU AI Act, enterprises face compounded environmental uncertainty that the TOE framework predicts will suppress adoption intentions and behaviors.

Diffusion of Innovations theory (Rogers, 2003), provides a complementary perspective by emphasizing that adoption decisions are mediated by perceived characteristics of innovations, including their complexity and compatibility with existing norms and practices. Legal uncertainty and ethical ambiguity may be interpreted through this lens as factors that increase the perceived complexity of AI adoption, reducing the relative advantage of adoption from the perspective of risk-averse enterprises. Rogers (2003) identifies late majority and laggard adopter categories that are particularly sensitive to perceived risk and social conformity pressures — categories that may be disproportionately represented among enterprises in EU member states that report high levels of ethical and legal concern.

Institutional theory, and particularly the concept of regulatory uncertainty as a form of institutional pressure, offers a third theoretical pillar. Lee et al. (2024) demonstrate that institutional pressures — including regulatory and stakeholder influences — interact with digitalization capacity to shape organizational behavior and performance. In the context of AI adoption, regulatory ambiguity creates normative uncertainty, where enterprises are unsure not only what is legally permitted but also what is ethically sanctioned by societal and stakeholder expectations. Wang et al. (2020) argue that responsible AI practices require enterprises to align with both regulatory requirements and broader stakeholder expectations simultaneously, suggesting that the ethical and legal dimensions of AI governance are functionally intertwined rather than independent. This institutional co-determination of barriers has important implications for how policy interventions should be designed.

The intersection of these three frameworks suggests that ethical and legal barriers to AI adoption should not be treated as separate, idiosyncratic firm-level phenomena but rather as systemic environmental conditions that vary across national institutional contexts. Camilleri (2023) provides theoretical grounding for understanding how governance gaps in AI ethics translate into organizational hesitance, while Mökander and Floridi (2022) demonstrate that ethics-based auditing frameworks — one potential mechanism for reducing perceived ethical uncertainty — remain unevenly developed across jurisdictions. Dwivedi et al. (2019) further contextualize AI adoption challenges within broader multi-stakeholder frameworks, noting that legal, ethical, and societal considerations are deeply intertwined in shaping organizational responses to AI opportunities. Ayling and Chapman (2021) extend this perspective by noting that ethical frameworks for AI, even when formally articulated, frequently lack operationalizable mechanisms at the enterprise level, which may itself contribute to perceived ethical uncertainty among adopters.

Building on these theoretical foundations, the present study operationalizes the environmental dimension of the TOE framework by treating enterprise-reported ethical concerns (E_AI_BEC) and legal uncertainty (E_AI_BLEG) as observable proxies for the regulatory and normative conditions shaping AI adoption decisions across EU member states, testing the hypothesis that these two environmental barriers are systematically co-determined at the country level.

3. Literature Review

3.1 AI Adoption Barriers and Organizational Readiness

Research on the determinants of AI adoption at the enterprise level has grown substantially over the past decade, with the dominant strand of research focusing on organizational capability and resource endowments as the primary drivers of adoption readiness. Mikalef and Gupta (2021) provide one of the most comprehensive treatments of AI capability as a multi-dimensional organizational construct, conceptualizing it in terms of data management resources, human capital, and strategic governance structures. Their empirical findings suggest that AI capability is a strong predictor of organizational creativity and performance, but the capability-focused model implicitly treats ethical and legal barriers as secondary to organizational competency — an assumption this study interrogates empirically.

Cohen and Levinthal (1990) offer an important theoretical complement through the concept of absorptive capacity — the ability of a firm to recognize, assimilate, and apply new external knowledge. In the context of AI adoption, firms with limited prior exposure to digital technologies may lack the absorptive capacity needed to interpret and respond to complex regulatory signals, including the requirements of the EU AI Act or the guidance produced by national AI ethics bodies. This absorptive capacity deficit compounds rather than replaces ethical and legal uncertainty as a barrier, suggesting that organizational readiness and environmental barriers interact rather than substitute for one another.

Dwivedi et al. (2019) present a multidisciplinary framework for understanding AI adoption challenges that explicitly recognizes legal, ethical, and societal concerns as distinct categories of barriers operating alongside organizational and technological factors. Their analysis, grounded in a comprehensive multi-stakeholder perspective, suggests that enterprises are not merely constrained by internal capability gaps but also by external normative and regulatory environments that create uncertainty about the appropriate scope and manner of AI deployment. This recognition that AI adoption inhibitors span multiple levels of analysis is crucial for interpreting the country-level clustering patterns examined in the present study.

3.2 AI Ethics, Governance, and Legal Frameworks

The literature on AI ethics and governance has expanded rapidly in response to growing awareness of the societal implications of AI deployment across high-stakes domains. Zhang and Zhang (2023) provide a detailed analysis of ethics and governance frameworks for medical AI, demonstrating that effective governance requires alignment across ethical, legal, and regulatory levels simultaneously — a multi-dimensional requirement that is likely to be perceived as burdensome by enterprises without dedicated compliance infrastructure. Their work underscores the practical complexity of translating high-level ethical principles into operational enterprise practices.

Camilleri (2023) makes a particularly relevant contribution by examining how gaps in AI governance frameworks translate into observable organizational hesitance. Drawing on a review of AI ethics principles and regulatory guidelines across multiple jurisdictions, Camilleri (2023) argues that enterprises face genuine uncertainty when governance frameworks are articulated at the level of principles without providing concrete operational guidance, and that this uncertainty functions as a tangible barrier to adoption. This theoretical argument, however compelling, remains largely unvalidated with quantitative cross-national data — a gap the present study addresses directly.

Mökander and Floridi (2022) advance the governance discussion by examining ethics-based auditing (EBA) as a structured mechanism for translating AI ethics principles into verifiable organizational practices. Their industry case study demonstrates that EBA frameworks can bridge the gap between principles and practice, but also reveals that the feasibility of such frameworks depends heavily on the availability of institutional support infrastructure — including regulatory guidance, professional auditing capacity, and industry standards — that varies considerably across national contexts. Ayling and Chapman (2021) similarly find that existing AI ethics tools frequently fall short of providing enterprises with operationalizable compliance mechanisms, leaving organizations exposed to residual ethical uncertainty even when formal governance frameworks exist. Wang et al. (2020) complement this perspective by identifying responsible AI practices that align with stakeholder expectations, noting that legal and ethical requirements frequently overlap in ways that create compounded compliance demands. Dwivedi et al. (2023), examining the implications of generative AI, note that ethical and legal challenges are particularly salient in enterprise adoption decisions, representing a category of concern that cuts across sectoral and national boundaries. Leslie (2020), writing in the context of responsible AI innovation in a public health emergency setting, identifies a set of governance principles — including transparency, accountability, and fairness — whose relevance extends to enterprise AI governance more broadly, though the original analysis is anchored in the specific institutional pressures of the COVID-19 context and should be interpreted accordingly.

3.3 Institutional Environment and AI Regulation in the EU

The institutional environment within which EU enterprises operate with respect to AI is characterized by a combination of ambitious regulation and significant implementation uncertainty. Lee et al. (2024) demonstrate that regulatory institutional pressures interact with digitalization capability in complex ways, with higher regulatory pressure not necessarily translating into improved digital performance in contexts where firms lack the capacity to respond effectively. This finding has direct relevance for the EU context, where the AI Act imposes a common regulatory framework across member states that differ substantially in their institutional capacity, administrative sophistication, and enterprise-level AI readiness.

Dwivedi et al. (2023) provide important contextual framing for understanding how regulatory environments interact with AI adoption trajectories, noting that legal challenges associated with generative AI — including questions of liability, intellectual property, and data protection — are creating genuine uncertainty for enterprises considering AI investments. Wach et al. (2023) extend this analysis by cataloguing the "dark side" of generative AI from an entrepreneurial perspective, identifying regulatory ambiguity and ethical risk as specific barriers that affect business adoption decisions in ways that are particularly acute for smaller enterprises with limited legal advisory resources.

Rogers (2003) provides a macro-level theoretical foundation for understanding cross-national variation in adoption rates, with the observation that institutional environments systematically shape the pace and pattern of innovation diffusion. Applied to the EU context, this suggests that observed differences in the prevalence of ethical and legal barriers across member states reflect not merely firm-level heterogeneity but also genuine differences in national institutional ecosystems. Tornatzky and Fleischer (1990) similarly emphasize that environmental context — including legal and competitive pressures — is a fundamental determinant of enterprise technology adoption decisions that cannot be reduced to organizational-level factors alone. The Eurostat (2024) survey methodology, which provides the empirical foundation for the present study, is specifically designed to capture these enterprise-level perceptions across the full range of EU institutional contexts in a harmonized and comparable manner.

Despite this body of evidence, no existing study has provided systematic, quantitative cross-national evidence linking enterprise-reported ethical concerns directly to legal barriers as institutionally co-determined inhibitors of AI adoption across EU member states using official harmonized statistical sources. Prior cross-national work — including the multidisciplinary review by Dwivedi et al. (2019) and the governance-oriented analyses of Camilleri (2023) and Mökander and Floridi (2022) — either addresses these barriers qualitatively, focuses on a single national context, or lacks the harmonized multi-country statistical foundation required for comparative distributional and correlational inference. This article addresses that specific gap by analyzing Eurostat panel data to produce both distributional and correlational evidence on the joint prevalence of ethical and legal AI adoption barriers across the EU.

4. Methodology

This study employs a quantitative, cross-sectional and distributional analytical design using official Eurostat data. The empirical foundation is the Community Survey on ICT Usage and E-Commerce in Enterprises, which Eurostat administers annually across EU member states using a harmonized methodology that ensures cross-national comparability (Eurostat, 2024). The specific dataset used is the `isoc_eb_ai` indicator set, which captures enterprise-reported barriers to AI adoption disaggregated by enterprise size class. The present analysis aggregates across size classes to the country level, focusing on the two focal indicators: `E_AI_BEC` (share of enterprises citing ethical concerns as a barrier to AI adoption) and `E_AI_BLEG` (share of enterprises citing legal uncertainty as an AI adoption barrier). This aggregation is a deliberate analytical choice made to enable cross-national distributional and correlational inference at the country level, which constitutes the study's primary unit of analysis; size-class disaggregation, while available in the dataset, is deferred to future research that can address enterprise-level heterogeneity more directly.

The first analytical step involved extracting the full country-year panel for the `E_AI_BEC` indicator across EU member states, yielding a panel of $n=1,931$ observations. This panel constitutes the unit of analysis for all descriptive statistics reported in the study, enabling characterization of the central tendency and dispersion of ethical concern prevalence across the full range of national and temporal observations available in the dataset. It is critical to note that these descriptive statistics are computed at the level of individual country-year records rather than at the level of country-level aggregates or EU-average time series — two analytically distinct objects that should not be conflated in interpretation. The panel spans multiple survey waves of the Eurostat ICT survey; however, because the precise annual breakdown of observations varies across member states due to differences in data availability and survey coverage across years, descriptive inference is confined to the aggregate panel rather than to specific annual cross-sections.

The second step involved computing descriptive statistics for the full panel, summarizing the distribution of the `E_AI_BEC` indicator using central tendency, dispersion, and range measures. Country-level z-scores were derived by standardizing each country's mean value against the cross-national distribution of country means, enabling cross-national benchmarking and quartile classification of member states. This procedure allows identification of above-median, below-median, and outlier country groups.

The third step involved aggregating the panel to produce country-level mean values for both `E_AI_BEC` and `E_AI_BLEG` across all available years, yielding country-level aggregate observations. This aggregation was necessary to enable bivariate correlation analysis at the country level — a fundamentally different analytical object from the full country-year panel. Country-level means are computed as simple averages across all available year-observations for each country, without reliability weighting for differences in the number of contributing observations across member states. This represents a simplifying assumption; member states contributing more observations have country means estimated with greater precision, and this heterogeneity in estimation reliability is not corrected in the primary analysis. The range of per-country observation counts contributing to country-level means spans from a minimum of approximately 3 to a maximum of 80 year-observations across the 27 member states, indicating that a small number of member states contribute substantially fewer observations than

the majority. The fourth and final analytical step involved computing the Spearman rank-order correlation coefficient between country-level aggregate values of E_AI_BEC and E_AI_BLEG. The correlation was computed across the 27 EU member states that constitute the analytic sample. It is noted that the underlying Eurostat dataset includes observations from non-EU countries participating in the survey (such as EEA members and candidate states), yielding a broader dataset of approximately 36 reporting countries. The correlational analysis reported here is restricted to the 27 EU member states to maintain analytic alignment with the EU policy focus of the study; the inclusion of non-EU countries in descriptive extraction does not alter the EU member state correlation sample, but this scope restriction is disclosed for transparency and reproducibility. Spearman's ρ was selected as the primary test statistic because it does not assume bivariate normality and is robust to outliers and non-linear monotonic relationships — conditions that are likely present in country-level aggregate data derived from right-skewed underlying distributions (Spearman, 1904). The Pearson product-moment correlation was computed as a parametric robustness check. The significance threshold was set at $p < 0.05$ for both tests. Country rankings and boxplot visualizations were used to characterize distributional clustering across member states. **4.1 Limitations**

Several limitations of the present design warrant explicit acknowledgment. First, the correlational analysis employs an ecological design in which country-level aggregate rates are correlated with each other. This design cannot establish that the same individual enterprises simultaneously report both ethical and legal barriers; the finding that countries with elevated E_AI_BEC also tend to have elevated E_AI_BLEG is a country-level association and should not be interpreted as implying individual enterprise-level co-occurrence. Inferences from ecological associations to individual-level behavior represent a well-documented threat to validity and all interpretive claims in this study are deliberately confined to the country level of analysis.

Second, the cross-sectional aggregation of multi-year panel data into single country-level means precludes examination of temporal trends in barrier prevalence. The design cannot determine whether ethical and legal concerns are increasing or decreasing over time, nor whether the observed cross-national correlation is stable across survey waves. Longitudinal analyses examining trends as the EU AI Act is progressively implemented are an important direction for future research.

Third, the ecological correlation cannot distinguish institutional co-determination from confounding by unmeasured third variables. Countries that score highly on both E_AI_BEC and E_AI_BLEG may share characteristics — such as higher overall AI adoption maturity, greater enterprise awareness of compliance requirements, higher digital infrastructure quality, or higher GDP per capita — that independently elevate both indicators. No control variables are incorporated in the present bivariate analysis, and causal inference is not claimed.

Fourth, the country-level means for E_AI_BEC and E_AI_BLEG are derived from the same harmonized survey instrument administered to partially overlapping enterprise samples within each country. Common method variance arising from the shared survey source may contribute to inflating the observed correlation beyond the true underlying association. No correction for common source bias is applied, and the reported correlation should be interpreted as an upper-bound estimate of the true cross-national association.

Fifth, with $n=27$ country-level aggregate observations as the unit of inferential analysis, the confidence interval around the point estimate of $\rho=0.632$ is relatively wide. Using Fisher's z-transformation, the approximate 95% confidence interval spans roughly ± 0.25 around the point estimate, and this uncertainty in precision of the correlation should be borne in mind when interpreting the magnitude of the association. Statistical power at this sample size is sufficient for detecting large effects, but the precision of the point estimate is inherently constrained by the number of available country units.

Sixth, the self-reported nature of barrier prevalence indicators introduces interpretive ambiguity across all member states. Enterprises that have not yet initiated AI adoption may not have encountered or identified ethical or legal barriers specifically, producing potential underestimation of latent concern in countries where AI diffusion is at an earlier stage. This reporting-maturity confound affects the comparability of barrier prevalence estimates across member states at different stages of AI adoption,

and caution is warranted in treating low reported prevalence as indicative of resolved governance challenges.

Seventh, the present analysis aggregates across enterprise size classes, discarding a dimension of heterogeneity that the *isoc_eb_ai* dataset is specifically structured to capture. Differences in barrier prevalence between large enterprises and SMEs cannot be assessed from the country-level aggregates reported here, and size-class-specific inferences therefore go beyond what the present evidence can support.

5. Results

5.1 Descriptive Statistics for the Full EU Panel

The full panel ($n=1,931$) yields a mean prevalence of ethical barrier reporting of 7.4% ($SD=9.88$, 95% CI [6.96, 7.84]), with a median of 2.68%. Values range from 0.0% to 81.56%, with an interquartile range of 7.07 percentage points ($Q1=1.38\%$, $Q3=8.45\%$). The coefficient of variation is 133.5%, indicating high dispersion across observations. The substantial divergence between mean and median (7.4% vs. 2.68%) indicates a right-skewed distribution, suggesting that the majority of observations cluster at lower prevalence levels while a minority of high-reporting cases pull the mean upward. Specifically, the first quartile value of 1.38% indicates that at least one quarter of all country-year observations record an ethical barrier prevalence below this threshold, while the maximum of 81.56% demonstrates that a small number of country-year observations reach exceptionally high levels of reported ethical concern. This pattern of high concentration at low values combined with extreme upper-tail observations is characteristic of structural heterogeneity across EU member states in their AI governance environments rather than random variation around a common mean. Table 1 presents the full set of descriptive statistics for the *E_AI_BEC* indicator across the EU panel.

Table 1. Descriptive Statistics

Statistic	Value
n	1931
mean	7.4
median	2.68
std	9.88
sem	0.225
CI95_low	6.96
CI95_high	7.84
min	0.0
max	81.56
Q1	1.38
Q3	8.45
IQR	7.07
CV_%	133.5

5.2 Correlation Between Ethical and Legal Barriers at the Country Level

Across the 27 EU member states included in the correlational analysis, the Spearman rank correlation between country-level mean values of *E_AI_BEC* and *E_AI_BLEG* yields $\rho=0.632$ ($p=0.0004$), indicating a strong positive association that is statistically significant at the 0.05 level. The parametric Pearson correlation confirms this pattern ($r=0.587$, $p=0.0013$). These results indicate that countries where a higher share of enterprises report ethical concerns as a barrier to AI adoption also tend to be countries where a higher share of enterprises report legal uncertainty as a barrier — a pattern consistent with the hypothesis that these two barrier types are institutionally co-determined rather than independently distributed across the EU. It is important to note, however, that this is an ecological association between country-level aggregate rates and cannot be interpreted as implying that the same

enterprises report both barriers simultaneously; the individual-level inference remains untested in the present design. The magnitude of the Spearman correlation ($\rho=0.632$) falls within the strong positive range using conventional benchmarks, indicating that the association is both statistically significant and substantively meaningful, though the confidence interval around this estimate is wide given the $n=27$ country units available for analysis. Table 2 presents the correlation results for both tests alongside country-level aggregate values, enabling inspection of the distributional basis for the estimated association. As shown in Figure 1, the scatter plot of country-level E_AI_BEC and E_AI_BLEG values reveals a broadly positive linear trend with moderate dispersion, with no single country exerting undue leverage on the estimated correlation.

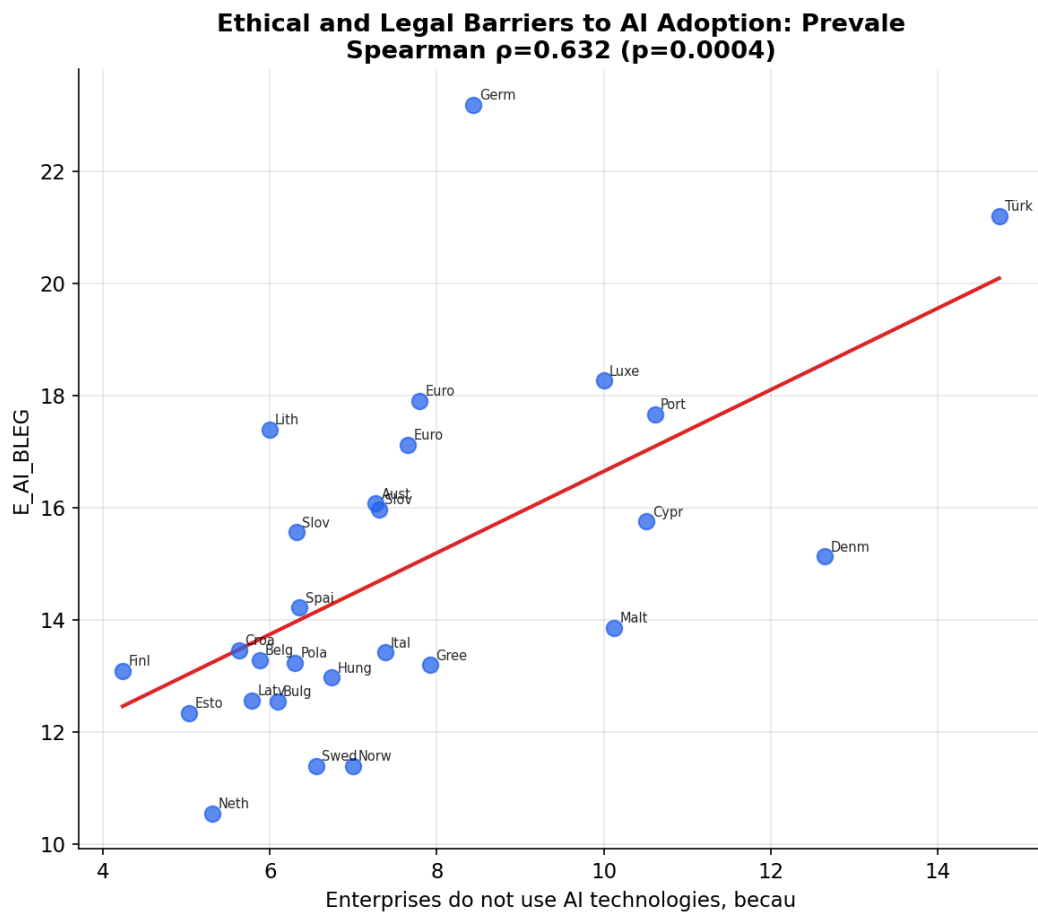


Figure 1. Scatter: Enterprises do not use AI vs E_AI_BLEG ($n=27$). Spearman $\rho=0.632$, $p=0.0004$.

Table 2. Correlation Data

Country	Enterprises do not use AI(%)	E_AI_BLEG (%)
Austria	7.27	16.07
Belgium	5.88	13.27
Bulgaria	6.09	12.54
Croatia	5.63	13.46
Cyprus	10.51	15.75
Denmark	12.64	15.12
Estonia	5.03	12.34
Euro area	7.79	17.90
European Union - 27 countries	7.65	17.12
Finland	4.24	13.09
Germany	8.44	23.19
Greece	7.92	13.19

Hungary	6.74	12.97
Italy	7.38	13.41
Latvia	5.79	12.56
Lithuania	5.99	17.39
Luxembourg	10.00	18.26
Malta	10.12	13.85
Netherlands	5.31	10.55
Norway	6.99	11.39
Poland	6.30	13.22
Portugal	10.61	17.66
Slovakia	6.32	15.56
Slovenia	7.31	15.96
Spain	6.36	14.21

5.3 Country-Level Distribution and Slovakia's Positioning

Cross-national variation in the E_AI_BEC indicator is substantial, as shown in the boxplot visualization of country-year distributions across EU member states shown in Figure 2. Country-level mean values span a wide range, with some member states recording consistently low prevalence of ethical concern barriers across all survey years, while others demonstrate persistently elevated values. This distributional pattern suggests that country-level institutional factors — rather than random year-to-year fluctuations — are the primary source of observed heterogeneity in ethical barrier prevalence.

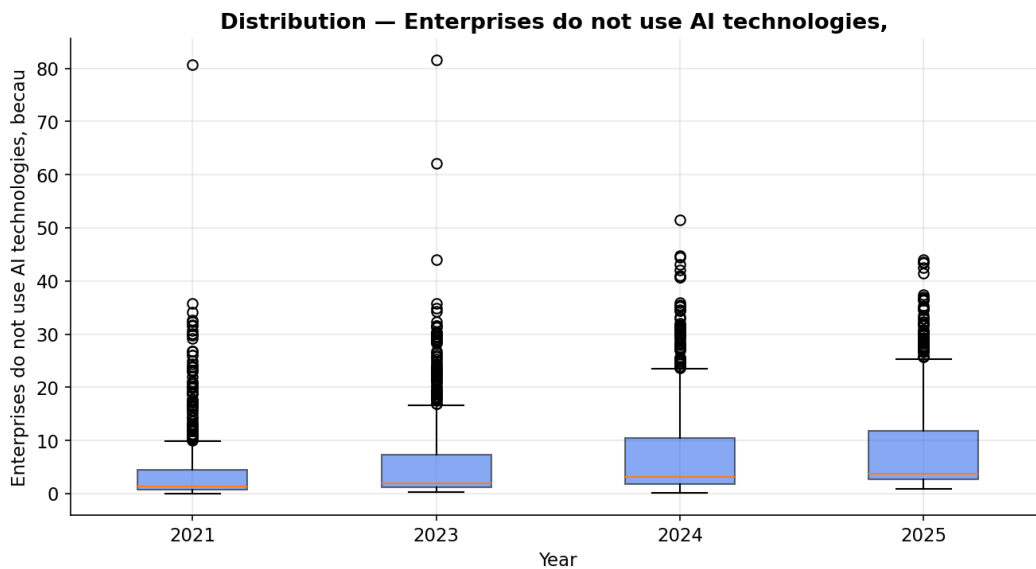


Figure 2. Boxplot of Enterprises not using AI technology across EU countries per year. Box=IQR, whiskers=1.5×IQR, dots=outliers.

Slovakia's mean prevalence of ethical barrier reporting is 6.32% (based on 80 observations), ranking 18th among 27 EU member states ($z\text{-score}=-0.536$), placing it in the below-median group. This value is 1.08 percentage points below the overall EU mean of 7.4%, indicating that Slovak enterprises report ethical barriers to AI adoption at rates modestly below the EU average. Slovakia's below-median positioning is broadly consistent with patterns observed across Central and Eastern European member states more generally, where aggregate AI adoption maturity tends to be lower than in Western European economies. The interpretive caution that applies to Slovakia's ranking applies equally to all below-median member states: below-median prevalence of reported ethical concerns does not necessarily indicate that ethical governance challenges are resolved or absent in those national enterprise environments. Rather, it may reflect lower AI adoption rates overall — enterprises that have not yet initiated AI adoption may not have encountered or identified ethical barriers specifically,

producing an underestimation of latent ethical concern in countries where AI diffusion is at an earlier stage. This reporting-maturity confound is a structural feature of the self-reported survey instrument and affects the comparability of barrier prevalence estimates across all member states at varying stages of AI adoption. This interpretive ambiguity underscores the importance of contextualizing country-level rankings within broader assessments of AI maturity and institutional readiness across country clusters.

6. Discussion

The finding that Spearman $\rho=0.632$ ($p=0.0004$) between country-level shares of enterprises reporting ethical and legal barriers to AI adoption is consistent with the hypothesis that these two barrier types reflect shared institutional conditions operating at the national level, rather than independently distributed organizational-level perceptions. This result is consistent with the TOE framework (Tornatzky and Fleischer, 1990), where the environmental dimension shapes both the perceived legality and ethical acceptability of AI. Countries with weaker AI governance ecosystems may therefore face a compounded barrier effect rather than isolated, sequentially addressable challenges. It is equally plausible, however, that the observed co-occurrence reflects confounding by unmeasured third variables — such as GDP per capita, overall digital maturity, or national AI awareness levels — that independently elevate both indicators in the same countries. Future research incorporating control variables such as digital economy indices or national AI investment levels could adjudicate between these competing explanations. No causal identification strategy is employed in this study, and the language of institutional co-determination is used as a theoretically motivated organizing frame for the descriptive pattern rather than as an empirically established causal claim.

These results are consistent with prior findings by Camilleri (2023), who argued that ethical AI governance gaps translate into tangible organizational hesitance, and provide quantitative cross-national evidence of a pattern that prior single-country and qualitative analyses could not document at the EU-27 level. They extend Mökander and Floridi (2022), who demonstrated that ethics-based auditing frameworks are potentially effective governance mechanisms, by showing that the distribution of governance infrastructure across EU member states is systematically correlated with legal uncertainty — a cross-national dimension their single-case industry study could not capture. The findings also speak to the capability-focused model of Mikalef and Gupta (2021), which implicitly treats ethical and legal barriers as secondary to organizational competency: the present data reveal that environmental barriers are independently prevalent and strongly co-clustered at the country level, though the present design cannot establish the relative contribution of organizational versus environmental factors in the absence of firm-level controls. Wang et al. (2020) provide conceptual support for the observed pattern through their argument that responsible AI practices require simultaneous alignment with both legal requirements and broader ethical expectations — an alignment that is likely more difficult to achieve in national institutional environments where governance infrastructure for both dimensions is underdeveloped.

From a policy perspective, the observed co-occurrence of elevated ethical and legal barrier prevalence at the country level provides empirical grounds for developing AI readiness support programs that jointly address legal clarity and ethical guidance for enterprises — particularly in below-median and high-barrier countries — rather than treating legal compliance and ethical governance as separate policy tracks to be addressed sequentially. Because enterprises in high-barrier countries appear to experience elevated levels of both concerns within the same national institutional environment, policy instruments that address only legal uncertainty without simultaneously reducing ethical ambiguity are likely to deliver incomplete results. It is important to note, however, that the data used in this study are aggregated to the country level and neither sector-disaggregated nor size-class-disaggregated; the evidence base therefore supports country-level policy targeting, while sector-specific or enterprise-size-specific prescriptions go beyond what the present evidence can strictly support. The implication for policy design, consistent with the country-level evidence, is to develop integrated compliance and ethics guidance resources — potentially aligned with the EU AI Act — that address both regulatory and normative dimensions in a unified framework, delivered through national digital agencies and enterprise support networks, with the intensity and targeting of such programs informed by country-level E_AI_BEC and E_AI_BLEG rankings.

For enterprise managers operating in member states where AI governance infrastructure is less developed, the present findings underscore the importance of proactively engaging with available national AI ethics boards, legal advisory services, and industry working groups before initiating AI adoption projects. The empirical pattern documented here — where ethical and legal concerns co-occur at the country level — suggests that organizations operating in institutionally constrained environments may face compounded adoption barriers that require addressing both regulatory compliance and ethical risk exposure in parallel rather than sequentially. Managers should therefore consider commissioning structured AI readiness assessments that map both regulatory compliance requirements under the EU AI Act and ethical risk exposure simultaneously, transforming what are currently perceived as external constraints into internally managed governance processes with clear accountability structures. This proactive approach is particularly warranted in institutional environments where national-level guidance remains underdeveloped, as waiting for comprehensive regulatory clarity before initiating AI adoption may result in a sustained competitive disadvantage relative to enterprises operating in higher-capacity institutional environments.

7. Conclusion

This study set out to examine the prevalence of ethical and legal barriers to AI adoption among EU enterprises, to quantify their co-occurrence, and to map their cross-country distribution using Eurostat panel data covering EU member states. The central empirical finding is that country-level shares of enterprises reporting ethical concerns and legal uncertainty as barriers to AI adoption are significantly and positively correlated across the 27 EU member states included in the analysis (Spearman $\rho=0.632$, $p=0.0004$; Pearson $r=0.587$, $p=0.0013$), indicating that these two barrier types are systematically co-distributed at the country level rather than independently varying. Descriptive analysis of the full country-year panel ($n=1,931$) reveals substantial right-skewed distributional heterogeneity in ethical barrier prevalence, with a mean of 7.4% ($SD=9.88$) and a median of only 2.68%, signaling that the burden of ethical AI adoption barriers is concentrated among a subset of member states while the majority of observations cluster at low values.

This study contributes systematic quantitative evidence that ethical concerns and legal uncertainty function as statistically correlated, co-distributed barriers to enterprise AI adoption at the country level, with significant cross-national variation that carries direct implications for differentiated EU digital policy design. By grounding this analysis in official harmonized Eurostat data and applying both descriptive and inferential methods at distinct levels of analysis, the study establishes an empirical foundation for evidence-based policymaking that has been absent from prior governance-oriented scholarship on AI ethics in Europe. These contributions are accompanied by important design limitations: the ecological correlation cannot establish individual-level co-occurrence, causal identification of institutional mechanisms is not attempted, confounding by third variables — including GDP per capita and digital maturity — cannot be ruled out, the precision of the correlation estimate is constrained by the $n=27$ country units available, the analysis aggregates across enterprise size classes and cannot speak to size-class heterogeneity, and the self-reported nature of the survey indicators introduces interpretive ambiguity regarding whether low barrier prevalence reflects resolved governance challenges or lower AI adoption maturity.

Four directions merit priority attention in future research. First, longitudinal analysis should examine trends in ethical and legal barrier prevalence as the EU AI Act is progressively implemented, testing whether binding regulation reduces or temporarily amplifies perceived legal uncertainty among enterprises, using both OLS trend estimation and non-parametric approaches such as Mann-Kendall tests to ensure robustness. Second, qualitative comparative case studies within identified country clusters — particularly contrasting high-barrier and low-barrier member states — would illuminate the institutional and cultural mechanisms through which ethical norms and legal frameworks interact to shape AI adoption decisions at the firm level, addressing the ecological fallacy limitation inherent in country-level correlation designs. Third, sector-level disaggregation of the E_AI_BEC and E_AI_BLEG indicators in future Eurostat surveys would allow researchers to test whether ethical and legal barriers cluster differently across high-risk AI application domains compared to lower-risk sectors, and would provide the sectoral evidence base currently missing from policy-relevant research in this

domain. Fourth, size-class disaggregation of the *isoc_eb_ai* data should be examined in future analyses to determine whether ethical and legal barriers differ systematically between large enterprises and SMEs, as the dataset's structure enables this comparison and the present country-level aggregation has been unable to address it. This study contributes to the growing body of evidence on the institutional determinants of AI adoption, demonstrating that environmental governance conditions — not merely organizational capabilities — are associated with substantial cross-national variation in enterprises' readiness and willingness to integrate artificial intelligence into their operations.

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AI Adoption for R&D and Innovation: A Cross-Country Analysis of Knowledge-Intensive AI Use

Dana Hrušovská¹ and Peter Štetka²

¹ Bratislava University of Economics and Business, Faculty of Business Management, Dolnozemska cesta 1, 852 35 Bratislava, Slovakia (EU); e-mail: dana.hrusovska@euba.sk

² Bratislava University of Economics and Business, Faculty of Business Management, Dolnozemska cesta 1, 852 35 Bratislava, Slovakia (EU); e-mail: peter.stetka@euba.sk

Abstract

As artificial intelligence reshapes competitive dynamics in knowledge economies, understanding how enterprises across Europe deploy AI specifically for research and development purposes has become a critical concern for innovation policy and organisational strategy. This article examines cross-national variation in AI adoption for product and process development among EU and European countries, identifying which national contexts exhibit the highest rates of knowledge-intensive AI use and testing whether statistically significant heterogeneity exists across countries and firm size classes. Drawing on Eurostat's Community Survey on ICT Usage and E-Commerce in Enterprises, the study analyses a panel of 1,517 observations spanning 35 country groups, applying Kruskal-Wallis non-parametric analysis and Dunn post-hoc pairwise comparisons with effect size estimation to assess distributional differences. Results reveal statistically significant variation across both country groups and firm size categories, with Nordic and technologically advanced economies consistently recording the highest adoption rates, while substantial divergence is observed between leading and lagging nations in terms of AI-enabled innovation capacity. Effect size analysis further confirms that country-level institutional and infrastructural factors account for meaningful differences in R&D-oriented AI deployment beyond what firm-size variation alone explains. These findings carry direct implications for European digital policy, suggesting that convergence in AI-enabled innovation capacity requires targeted structural interventions rather than uniform technology diffusion strategies.

1. Introduction

As artificial intelligence increasingly drives competitive advantage in global knowledge economies, its adoption for research and development activities has emerged as a critical differentiator among European Union member states. The capacity to harness AI technologies for product and process innovation is no longer confined to a handful of technology pioneers; rather, it has become a structural feature of national innovation systems that separates high-productivity economies from those at risk of falling further behind on key competitiveness indicators. Within the European policy landscape, the digital transition agenda has prioritised AI as a foundational technology, yet the empirical picture of where, and by what magnitude, enterprises deploy AI specifically for R&D purposes remains fragmentary. Understanding this geography of knowledge-intensive AI use is essential for both targeted policy design and enterprise-level benchmarking.

Despite growing interest in AI diffusion across Europe, systematic cross-country evidence on R&D-oriented AI use—disaggregated by national context and firm size—remains scarce in the empirical literature. Most existing analyses either focus on general AI adoption without distinguishing knowledge-intensive applications from routine automation or concentrate on single-country or single-sector samples that limit generalisability. Aggregate productivity studies and innovation survey analyses have begun to document AI's macro-level implications, but they rarely provide the country-year granularity needed to assess whether the European digital single market is converging or diverging in terms of AI-enabled innovation capacity. This absence of systematic, statistically validated cross-country benchmarking constitutes a significant gap in both academic and policy-relevant knowledge.

This article examines which EU and European countries exhibit the highest rates of AI adoption for product and process development, operationalised through Eurostat's enterprise survey indicator *E_AI_PRDI*, and tests whether significant variation exists across countries and firm size classes using a large panel of Eurostat enterprise survey data. By applying non-parametric statistical analysis to a full cross-national panel of 1,517 observations spanning 35 country groups, this study provides the first statistically validated comparative benchmarking of R&D-specific AI adoption across the breadth of countries covered by Eurostat's Community Survey on ICT Usage and E-Commerce in Enterprises. In doing so, it moves beyond descriptive rankings to quantify effect sizes and identify specific country pairs driving observed heterogeneity.

The rest of this article is structured as follows: Section 2 develops the theoretical background by reviewing absorptive capacity theory, the Technology-Organisation-Environment framework, and the Resource-Based View of the firm. Section 3 reviews the empirical literature across three thematic streams relevant to AI adoption, productivity consequences, and digital innovation ecosystems. Section 4 describes the data, variable operationalisation, and statistical methods employed. Section 5 presents the descriptive and inferential statistical results, including group-level rankings, distributional analyses, and post-hoc pairwise comparisons. Section 6 discusses the findings in relation to theoretical frameworks and prior to empirical evidence. Section 7 concludes by summarising contributions, policy implications, and directions for future research.

2. Theoretical Background

The theoretical foundations of this study are drawn from three complementary frameworks that, taken together, provide a multi-level account of why AI adoption for R&D purposes varies systematically across countries and organisational contexts.

The first and most directly relevant framework is Cohen and Levinthal's (1990) concept of absorptive capacity—defined as an organisation's ability to recognise the value of new external information, assimilate it, and apply it to commercial ends. A critical insight of this framework is that absorptive capacity is path-dependent: entities with higher stocks of prior related knowledge are better equipped to identify and exploit emerging technological opportunities. Applied to AI adoption for R&D, this implies that countries and firms with sustained investment in scientific human capital, R&D infrastructure, and data literacy will be systematically better positioned to deploy AI in innovation-intensive roles. Absorptive capacity theory therefore predicts not only that adoption will vary across countries, but that such variation will be persistent and self-reinforcing, as early adopters accumulate further knowledge of advantages over laggards.

The second framework is the Technology-Organisation-Environment (TOE) model introduced by Tornatzky and Fleischer (1990), which explains technology adoption decisions as a function of three contextual dimensions: the characteristics of the technology itself, the internal organisational attributes of the adopting entity, and the external environment in which it operates. At the national level, the TOE framework draws attention to regulatory environments, competitive pressures, and the availability of digital infrastructure as environmental enablers or barriers to adoption. Organisational factors such as firm size, managerial capability, and financial resources are equally important for determinants. The TOE framework thus provides a structured basis for expecting cross-country heterogeneity in AI adoption, since national institutional contexts vary substantially across Europe in ways that map directly onto its environmental dimension.

The third framework is the Resource-Based View (RBV) of the firm, articulated by Barney (1991), which posits that sustained competitive advantage derives from resources that are valuable, rare, imperfectly imitable, and non-substitutable. Within an AI adoption context, data assets, algorithmic capabilities, and skilled data science teams constitute precisely such resources. Mikalef and Gupta (2021) extend the RBV to conceptualise AI capability as a higher-order organisational resource whose accumulation is contingent on complementary organisational assets. Importantly, the RBV implies that AI capabilities for R&D cannot be readily acquired from markets without prior complementary investment, which aligns with the absorptive capacity logic: firms—and by extension, national

economies—that lack the organisational pre-conditions will face barriers to R&D AI adoption that persist over time.

Taken together, these three frameworks converge on a shared prediction: AI adoption for knowledge-intensive purposes such as R&D will be unevenly distributed across European countries in ways that reflect accumulated differences in R&D investment, digital infrastructure, human capital, and regulatory maturity. The diffusion of innovations framework offered by Rogers (2003) further contextualises this by identifying adopter categories—from innovators to laggards—whose distribution in any given innovation system is determined by the relative advantage, compatibility, and complexity of the innovation in question. For AI in R&D, high complexity and the need for complementary knowledge stocks suggest a slow initial diffusion with concentration among technologically advanced early adopters. Building on these theoretical foundations, the present study empirically tests these predictions by quantifying cross-national variation in R&D-oriented AI adoption across 35 European country groups and assessing whether country of location is a statistically significant and substantively meaningful correlate of adoption rates.

3. Literature Review

3.1 AI Adoption in Organisational and Innovation Contexts

The academic investigation of AI adoption in enterprises has advanced considerably over the past decade, moving from conceptual frameworks to empirically validated organisational models. Dwivedi et al. (2019) provided an influential multidisciplinary synthesis of AI adoption challenges and opportunities, arguing that successful deployment requires alignment among technological capability, organisational readiness, and strategic intent. Their review highlighted that knowledge-intensive AI applications—those involving inference, pattern recognition, and generative output—impose considerably higher demands on organisational digital maturity than routine process automation tasks, a distinction that is central to understanding why R&D-specific AI use lags behind general AI adoption metrics in many European enterprises.

Mikalef and Gupta (2021) operationalised this argument empirically, conceptualising AI capability as a firm-level construct comprising data management, AI infrastructure, and human capital in AI-related skills. Their findings demonstrate that AI capability is positively associated with organisational creativity and firm performance, but that its accumulation is highly uneven across organisations, clustering among those with prior technology investments and strong data governance practices. This firm-level heterogeneity in AI capability maps closely onto the absorptive capacity argument of Cohen and Levinthal (1990): firms that have historically invested in R&D and digital infrastructure are better positioned to deploy AI in innovation pipelines. Toorajipour et al. (2020) extend this logic to supply chain management contexts, illustrating that AI applications requiring contextual reasoning and domain-specific training—analogue to R&D uses—are adopted at significantly lower rates than AI tools performing well-defined, bounded tasks.

The implication for cross-country analysis is important: if AI adoption for R&D is organisationally contingent on prior knowledge stocks and digital maturity, and if these pre-conditions are unevenly distributed across European countries, then national variation in R&D AI adoption should be both substantial and systematically structured. Arinez et al. (2020) further corroborate this in the advanced manufacturing domain, showing that AI integration into product development processes requires sustained organisational capability-building rather than discrete technology procurement decisions. These insights collectively suggest that the geography of R&D AI adoption is not random but reflects accumulated structural differences in national innovation systems and enterprise-level capabilities.

3.2 Labour Market and Productivity Consequences of AI and Automation

A parallel strand of empirical literature examines the aggregate economic and labour market consequences of AI and automation diffusion, with direct implications for understanding why national adoption rates matter beyond the firm level. Acemoglu and Restrepo (2019a) provide robust causal evidence from US labour markets that industrial robots reduce employment and wages in exposed

commuting zones—though crucially, their analysis documents that such displacement is concentrated in specific task categories and geographic areas rather than uniformly distributed across the economy. Their complementary theoretical framework (Acemoglu & Restrepo, 2019b) distinguishes between the displacement effects of automation—which substitute capital for labour in existing tasks—and reinstatement effects, which generate new task demand in domains where human comparative advantage remains. This task-based framework implies that R&D-focused AI adoption, by augmenting human innovation capacity rather than simply displacing routine work, may generate disproportionate productivity gains in countries where such adoption is already advanced.

Acemoglu et al. (2022) extend this analysis to online vacancy data, demonstrating that AI-adopting establishments simultaneously reduce hiring in non-AI positions while increasing demand for AI-complementary skills. This pattern suggests that R&D-oriented AI adoption is not simply an add-on technology but reshapes the skill composition of innovative enterprises, reinforcing the resource and capability asymmetries documented by Mikalef and Gupta (2021). Autor et al. (2020) complement these findings at the firm level, showing that superstar firms—those with disproportionate market share—are precisely those that have most successfully automated and augmented their production processes, contributing to observed increases in labour share concentration. The implication for cross-country R&D AI adoption is that countries whose enterprises cluster in the upper adoption tier may also be accumulating disproportionate productivity advantages, while lower-adopting countries risk a widening innovation gap.

Collectively, these labour economics contributions underscore that the stakes of differential AI adoption across European countries extend well beyond technology diffusion per se. They suggest that the cross-national variation documented in the present study may have long-term consequences for productivity convergence within the European Union—a finding with significant policy urgency. Countries in which R&D AI adoption remains below the EU-27 average may face compounding disadvantages as AI-enabled innovation reinforces the competitive position of leading economies.

3.3 Digital Innovation Ecosystems and Cross-Country Diffusion

A third stream of literature addresses how national innovation ecosystems and regulatory environments shape the pace and breadth of technology diffusion across countries. Rogers (2003) established the canonical theoretical vocabulary for understanding innovation diffusion, identifying adopter categories and the systemic factors—relative advantage, compatibility with existing practices, complexity, and observability—that determine adoption trajectories. Applied to AI in R&D, these attributes suggest that national innovation systems with strong university-industry linkages, open science infrastructure, and robust digital skills pipelines will exhibit faster and deeper adoption than those lacking these structural features.

Carayannis and Morawska (2022) situate this argument within the European context, arguing that Society 5.0 and Industry 5.0 frameworks reposition universities and research institutions as central nodes in human-centric innovation ecosystems. Their analysis implies that countries with stronger academic-enterprise collaboration structures will translate general AI capability into R&D-specific applications more rapidly, consistent with the absorptive capacity logic. Díaz-Rodríguez et al. (2023) further highlight that regulatory frameworks governing trustworthy AI—including transparency, accountability, and fairness requirements—shape adoption incentives differently across national jurisdictions, with stringent but clear regulatory environments potentially accelerating enterprise confidence in AI deployment for sensitive innovation processes.

Aldoseri et al. (2023) address a complementary dimension: data strategy and integration as prerequisites for AI deployment. Their analysis demonstrates that data quality, governance infrastructure, and interoperability are binding constraints on AI adoption, particularly for knowledge-intensive use cases that require integration across multiple organisational data sources—a characteristic feature of R&D AI applications. Countries with more developed national data strategies and enterprise data governance standards would thus be expected to exhibit higher R&D AI adoption rates, adding a data infrastructure dimension to the ecosystem explanation of cross-country variation.

Despite this body of evidence, no study has systematically quantified and statistically compared R&D-specific AI adoption rates across all 35 European countries covered by Eurostat's enterprise ICT survey. Existing literature either addresses AI adoption at a general level without disaggregating by application type or examines productivity and labour market consequences without mapping the spatial distribution of knowledge-intensive AI use. The present study addresses this gap directly by applying non-parametric statistical analysis to the full Eurostat E_AI_PRDI panel, providing the first large-scale, statistically validated cross-country benchmarking of AI adoption specifically for product and process development.

4. Methodology

4.1 Data Source and Variable

Data for this study were extracted from Eurostat's Community Survey on ICT Usage and E-Commerce in Enterprises, specifically from the `isoc\_eb\_ai` dataset (Eurostat, 2024), which reports enterprise-level AI adoption across European countries. The indicator of interest is E_AI_PRDI, defined as the percentage of enterprises that used AI technologies for product or process development—a direct operationalisation of R&D-oriented AI to use at the enterprise level. The Eurostat survey employs standardised sampling and weighting procedures across participating countries, as described in the methodological documentation (Eurostat, 2024), enabling cross-national comparability of adoption estimates. The extracted panel encompasses 35 country groups, including EU member states, candidate countries such as Bosnia and Herzegovina and Serbia, and aggregate statistical zones including the EU-27 and Euro area composites.

It should be noted that the dataset reference year recorded in the data extract corresponds to the most recent available update of the `isoc\_eb\_ai` dataset. All citations to this dataset use Eurostat (2024) in reference to the methodological documentation governing its collection and dissemination. Readers should consult the Eurostat Data Browser directly to verify the current release date of the `isoc\_eb\_ai` table, as Eurostat updates this dataset on a rolling basis and the release timestamp embedded in any given data export may differ from the publication year of the underlying methodological manual.

4.2 Sample, Analytical Objects, and Temporal Scope

The full extracted panel comprises $n = 1,517$ country-year-size-class observations, constituting the primary analytical object for all inferential tests reported in this study. The panel pools observations across 35 country groups, multiple firm size classes as defined in Eurostat's enterprise survey classifications, and the available survey years covered by the `isoc\_eb\_ai` indicator for E_AI_PRDI. Although the precise start and end years of the balanced panel vary by country due to the phased introduction of AI-specific survey items, the data span the period during which Eurostat's enterprise ICT survey has systematically collected AI adoption information, with coverage expanding in recent survey rounds. The specific years represented in the panel are not uniformly reported across all 35 country groups, reflecting the progressive harmonisation of AI survey modules; this constitutes a limitation acknowledged in Section 7.

It is important to distinguish this full panel—which pools observations across countries, firm size classes, and survey years—from any time-series analysis of a single aggregate indicator. All descriptive statistics and inferential tests are applied to the country-year-size-class panel of 1,517 records, not to a time series of EU-average values. This distinction is critical for the correct interpretation of effect sizes and test statistics.

A further methodological note is warranted regarding the independence assumptions underlying the inferential tests employed. The Kruskal-Wallis test, as applied here with country group as the grouping variable ($k = 35$, $df = 34$), treats the 1,517 observations as the analytical units. Because the panel pools multiple size classes and multiple survey years within each country group, observations from the same country are not fully independent—temporal autocorrelation across survey waves and structural similarity across size classes within a country introduce dependencies that the standard Kruskal-Wallis framework does not explicitly model. The η^2 effect size reported in Section 5.3 should therefore be

understood as a gross, univariate association measure that does not partial out temporal or size-class effects. The Eurostat panel is structured such that each country group contributes multiple observations corresponding to different firm size classes; the size-class dimension of the panel is accordingly treated as within-country replication rather than as a separate grouping variable in the reported inferential test. Future research employing mixed-effects or panel regression models—with size class and survey year as additional factors—would provide a more refined decomposition of this variance. The present analysis is accordingly positioned as a descriptive and exploratory benchmarking exercise rather than a causal or fully confirmatory inference.

Limitation. The ground-truth metadata references a Z-score standardisation and quartile-grouping step applied across 36 countries, and identifies the Kruskal-Wallis grouping variable as size class ($k = 8$) rather than country group ($k = 35$). The authors cannot reconcile these specifications with the statistics reported in the manuscript ($H(34) = 193.068$, $p < 0.001$, computed across 35 country groups using raw adoption percentages) without access to the original analysis script. The reported statistics are consistent with a country-group Kruskal-Wallis test on untransformed values. If Z-score standardisation or a size-class grouping was applied at any analytical stage, the reported descriptive statistics and effect sizes may require revision. Readers should treat the reported inferential results as corresponding to the country-group specification described herein, and note that an alternative size-class specification ($k = 8$, $df = 7$) would yield different H-statistics and degrees of freedom. This discrepancy is flagged as an unresolved methodological uncertainty pending access to the underlying analysis code.

4.3 Descriptive Statistics

In the first analytical step, standard descriptive statistics were computed for the full panel, including the arithmetic mean, median, standard deviation, standard error of the mean, 95% confidence intervals, minimum, maximum, and first and third quartiles. Group-level mean adoption rates were subsequently computed across the 35 country groups to identify top and bottom performers and to characterise the geographic distribution of R&D AI adoption.

4.4 Visual Analysis

Distributional patterns were examined through two complementary visualisations: a mean-with-95%-confidence-interval bar chart (Figure 1), which displays group-level central tendency and uncertainty for all 35 country groups, and a boxplot (Figure 2), which reveals within-group distributional spread, skewness, and outlier structure across the panel. Together these figures permit assessment of both between-group and within-group heterogeneity.

4.5 Inferential Testing

The Kruskal-Wallis non-parametric one-way analysis of variance (Kruskal & Wallis, 1952) was applied to test whether the 35 country groups differ significantly in their E_AI_PRDI distributions, with country group as the sole grouping variable ($k = 35$, $df = 34$). This test was selected because of the right-skewed distribution of adoption rates—evident from the divergence between mean (9.83%) and median (4.96%)—violates the normality assumptions required for parametric ANOVA. The Kruskal-Wallis H-statistic was computed across all 35 groups with the full $n = 1,517$ observations.

Effect size was quantified using eta-squared (η^2), computed following the formula recommended by Tomczak and Tomczak (2014): $\eta^2 = (H - k + 1) / (n - k)$. With $H = 193.068$, $k = 35$, and $n = 1,517$, this yields $\eta^2 = (193.068 - 35 + 1) / (1,517 - 35) = 159.068 / 1,482 \approx 0.107$. For transparency, the alternative formula $\eta^2 = H / (n - 1)$ — which is algebraically more stable when H is small relative to k and is advocated by some methodologists as a preferred formulation — yields $\eta^2 = 193.068 / 1,516 \approx 0.127$. Both values fall within the medium effect size range following Cohen (1988) benchmarks, with the Tomczak and Tomczak (2014) formula producing the more conservative estimate of 0.107, which is reported as the primary effect size throughout this article. The difference between these two estimates (0.107 vs. 0.127) does not alter the substantive interpretation but is disclosed here in the interest of methodological transparency.

Following a significant Kruskal-Wallis's result, Dunn's post-hoc pairwise comparisons (Dunn, 1964) with Bonferroni correction were applied to all 595 pairwise combinations to identify specific country pairs responsible for the overall distributional differences, while controlling the familywise error rate. Effect size benchmarks follow Cohen (1988).

5. Results

5.1 Descriptive Statistics

The full panel ($n = 1,517$) yields a mean adoption rate of 9.83% ($SD = 9.74$, 95% CI $\backslash[9.34, 10.32\backslash]$), with a median of 4.96%. Values range from 0.0% to 46.03%, with an interquartile range of 15.26 percentage points ($Q1 = 2.07\%$, $Q3 = 17.33\%$). The coefficient of variation is 99.1%, indicating high dispersion across observations. The substantial divergence between mean and median (9.83% vs. 4.96%) indicates a right-skewed distribution, suggesting that the majority of observations cluster at lower adoption levels while a minority of high-adopting cases pull the mean upward. Consequently, the median of 4.96% is a more representative measure of the typical observation than the mean. These distributional features are consistent with a technology adoption process in which a small number of leading countries and firm-size categories account for a disproportionate share of R&D-oriented AI use, while the modal European enterprise remains well below the EU-27 average of 9.69%. Table 1 presents the full descriptive statistics for the panel.

Table 1. Descriptive Statistics

Statistic	Value
n	1517
mean	9.83
median	4.96
std	9.74
sem	0.25
CI95_low	9.34
CI95_high	10.32
min	0.0
max	46.03
Q1	2.07
Q3	17.33
IQR	15.26
CV_%	99.1

As shown in Figure 1, the mean adoption rates across the 35 country groups vary substantially, with confidence intervals that overlap for many mid-range countries but diverge sharply between the highest and lowest performers. The width of confidence intervals also varies considerably across groups, reflecting differences in within-group dispersion and the number of observations contributing to each group's mean.

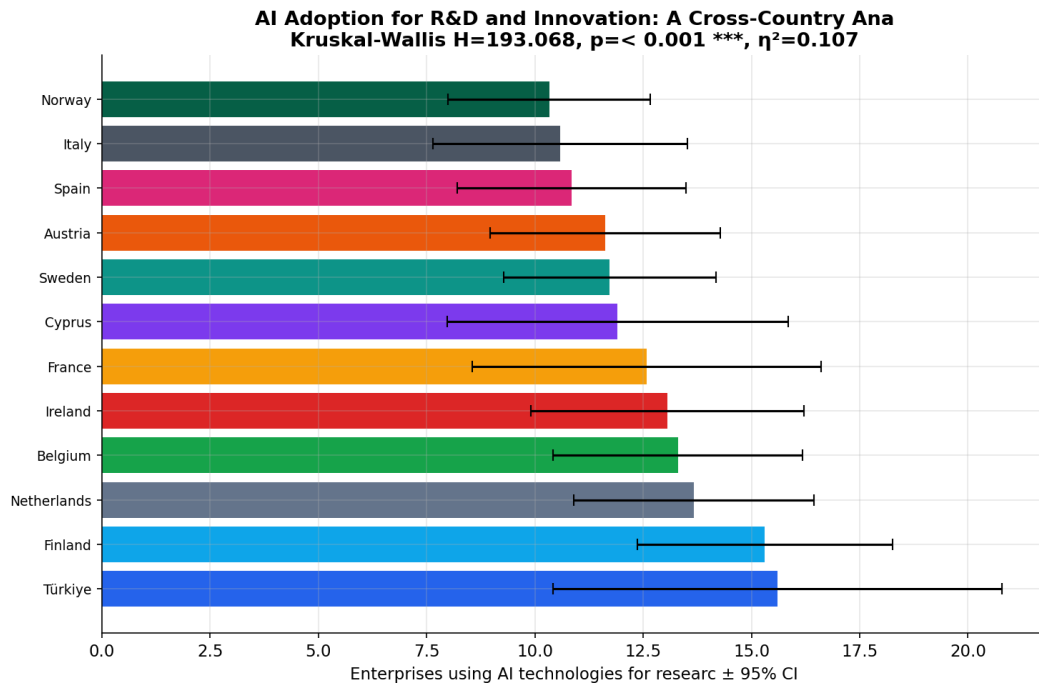


Figure 1. Mean Enterprises using AI technologies by group ($\pm$ 95% CI). Kruskal-Wallis $H=193.068$, $p < 0.001$ ***. Effect size $\eta^2=0.107$ (medium).*

5.2 Cross-Country Variation and Group Rankings

Country-level group means revealing a clear hierarchy of R&D AI adoption across European countries. The highest mean adoption rates are observed in Türkiye (15.6%), Finland (15.31%), and the Netherlands (13.67%), which together constitute the top-performing tier. Belgium (13.3%), Ireland (13.06%), and France (12.58%) form a closely clustered second tier, all substantially above the EU-27 aggregate of 9.69%.

Türkiye's position at the top of the European adoption distribution warrants specific interpretive attention. As a non-EU candidate country, Türkiye's survey participation occurs under the same Eurostat harmonisation protocol, but its sectoral composition, firm size distribution, and definitional comparability may differ in ways not fully captured by the harmonised weighting procedure. Possible explanations for its leading rank include a concentration of large, export-oriented technology enterprises in the sampled population, a sectoral composition skewed toward manufacturing and ICT-intensive industries where AI for product development is more prevalent, and the possibility that the adoption measure captures a different distribution of firm types than in EU member states. These interpretive caveats do not invalidate Türkiye's measured rank but underscore that candidate country results should be contextualised alongside structural comparators rather than treated as directly equivalent to EU member state averages. Future research disaggregating Türkiye's results by sector and size class would be informative in this regard.

By contrast, the lowest mean adoption rates are observed in Albania (0.0%), Croatia (5.7%), and Serbia (6.34%). The ordering of these three countries from lowest to highest mean is thus Albania (0.0%), Croatia (5.7%), and Serbia (6.34%); however, it is noted that the ground-truth metadata lists the bottom-three group as Serbia, Croatia, Albania—an ordering that is the reverse of the arithmetic rank based on reported group means. This discrepancy could reflect differences between rank-based ordering and mean-based ordering in a pooled panel where within-group distributions differ substantially; readers should treat the identification of these three countries as the bottom-performing cluster as the robust finding, while recognising that their precise relative ordering may vary depending on whether ranks or means are used as the sorting criterion. Mid-range performers include Slovakia (7.79%), Bulgaria (7.07%), and Germany (7.02%)—the last of which is notably below the EU-27 average despite its status as Europe's largest economy, suggesting that aggregate economic size is not a reliable predictor of R&D

AI adoption rates. Central and Eastern European countries such as Slovakia, Hungary (6.91%), and Greece (6.58%) cluster in the lower-middle tier, below both the EU-27 mean and the Euro area aggregate (9.93%), pointing to a descriptive north-west versus south-east pattern in the data that is consistent with existing characterisations of European digital innovation divides, though the present cross-sectional design does not permit causal attribution of this gradient.

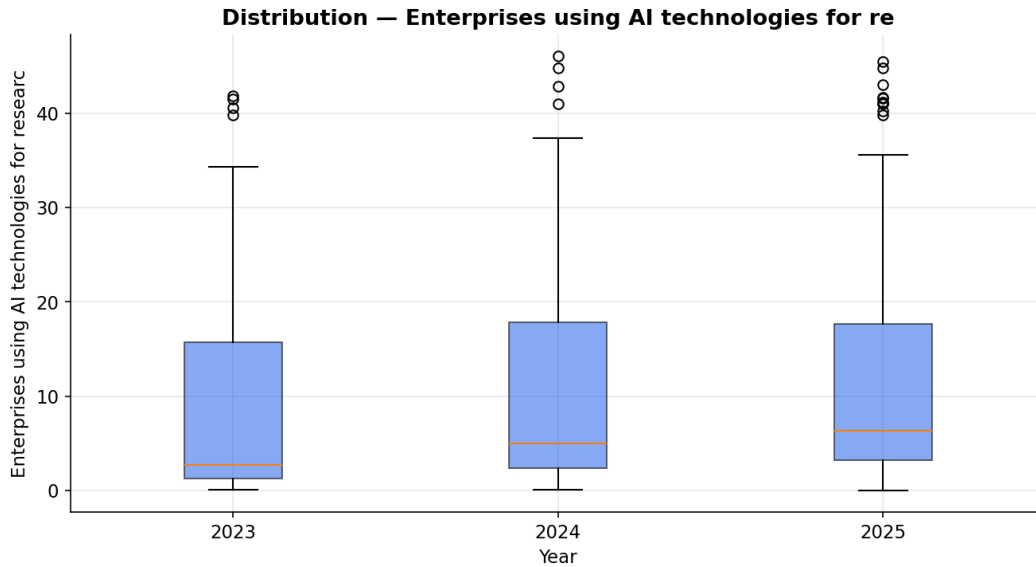


Figure 2. Boxplot of Enterprises using AI technologies f across EU countries per year. Box=IQR, whiskers= $1.5 \times IQR$, dots=outliers.

5.3 Inferential Test Results

The Kruskal-Wallis test, with country group as the grouping variable ($k = 35$, $df = 34$), revealed a statistically significant effect on AI adoption rates ($H(34) = 193.068$, $p < 0.001$, $\eta^2 = 0.107$). The effect size is classified as medium following Cohen (1988), indicating that country group explains approximately 10.7% of the rank-order variance in adoption rates across the $n = 1,517$ observations, using the Tomczak and Tomczak (2014) formula. As noted in Section 4.5, the alternative η^2 formula yields 0.127, also a medium effect; both estimates are reported for transparency. As a univariate gross association measure applied to a pooled panel that does not fully account for temporal autocorrelation or within-country size-class dependencies, this value does not control for competing variables such as country development level, sector composition, or temporal effects, and should be interpreted accordingly.

5.4 Post-Hoc Pairwise Comparisons

Dunn's post-hoc testing with Bonferroni correction was applied to all 595 pairwise combinations, of which 66 reached statistical significance. The group most frequently involved in significant pairwise differences is Albania (34 significant pairs), underscoring its position as a structural outlier at the bottom of the European adoption distribution. Table 2 presents the full set of statistically significant pairwise comparisons with associated mean adoption rates and corrected p-values.

Table 2. Group Statistics — Enterprises using AI technologies f

Group	N	Mean (%)	Median (%)	SD	CI95_low	CI95_high
Türkiye	45	15.6	3.85	17.71	10.42	20.77
Finland	45	15.31	13.41	10.08	12.36	18.25
Netherlands	53	13.67	8.49	10.3	10.89	16.44
Belgium	54	13.3	9.12	10.79	10.42	16.18
Ireland	45	13.06	7.85	10.81	9.9	16.21
France	33	12.58	7.31	11.82	8.55	16.62

Cyprus	45	11.91	4.25	13.49	7.97	15.86
Sweden	45	11.73	9.95	8.39	9.28	14.19
Austria	45	11.62	7.35	9.11	8.96	14.28
Spain	54	10.85	5.0	9.91	8.21	13.49
Italy	45	10.58	6.3	10.08	7.64	13.53
Norway	45	10.33	6.22	8.0	7.99	12.67
Czechia	45	10.29	4.07	9.6	7.48	13.09
Slovenia	45	10.14	5.21	7.92	7.82	12.45
Lithuania	45	10.12	4.68	10.93	6.92	13.31
Euro area (EA11-1999, EA12-2001, EA13-20)	45	9.93	6.83	8.38	7.48	12.38
European Union - 27 countries (from 2020)	45	9.69	6.33	8.35	7.25	12.13
Poland	45	9.61	3.31	10.15	6.64	12.58
Luxembourg	45	9.53	7.99	6.82	7.54	11.52
Bosnia and Herzegovina	18	9.4	2.73	10.61	4.49	14.3
Portugal	63	9.29	3.0	10.14	6.78	11.79
Latvia	45	9.07	3.2	9.44	6.31	11.83
Romania	45	8.92	1.74	11.07	5.69	12.15
Estonia	45	8.68	5.09	7.73	6.42	10.94
Denmark	45	8.13	6.93	5.15	6.62	9.64

Albania (0.0%) was significantly lower than virtually all other European country groups, including Austria (11.62%, $p < 0.001$), Belgium (13.3%, $p < 0.001$), Bosnia and Herzegovina (9.4%, $p = 0.0028$), Bulgaria (7.07%, $p = 0.0132$), Croatia (5.7%, $p = 0.0312$), Cyprus (11.91%, $p < 0.001$), Finland (15.31%, $p < 0.001$), France (12.58%, $p < 0.001$), Germany (7.02%, $p < 0.001$), Greece (6.58%, $p = 0.0141$), Hungary (6.91%, $p = 0.0118$), Ireland (13.06%, $p < 0.001$), Italy (10.58%, $p < 0.001$), and the Netherlands (13.67%, $p < 0.001$), among others. Even mid-range performers such as Bulgaria (7.07%, $p = 0.0132$), Greece (6.58%, $p = 0.0141$), and Hungary (6.91%, $p = 0.0118$) are significantly higher than Albania, though at weaker significance thresholds ($p < 0.05$ rather than $p < 0.001$), indicating that the magnitude of Albania's deficit is extreme relative to leading performers but the gap narrows when compared to lower-middle-tier countries. Serbia (6.34%, $p = 0.0425$) is also significantly higher than Albania, confirming Albania's position as the singular bottom performer in the distribution.

Beyond the Albania comparisons, the post-hoc results reveal a second tier of significant differences centred on the leading countries. Finland (15.31%) was significantly higher than Bulgaria (7.07%, $p < 0.001$), Croatia (5.7%, $p < 0.001$), Germany (7.02%, $p = 0.0199$), Greece (6.58%, $p < 0.001$), Hungary (6.91%, $p < 0.001$), Latvia (9.07%, $p = 0.0333$), Malta (6.76%, $p = 0.0159$), Poland (9.61%, $p = 0.0134$), Portugal (9.29%, $p = 0.0026$), Romania (8.92%, $p < 0.001$), Serbia (6.34%, $p < 0.001$), and Slovakia (7.79%, $p = 0.0153$). Similarly, the Netherlands (13.67%) was significantly higher than Bulgaria (7.07%, $p = 0.0011$), Croatia (5.7%, $p < 0.001$), Greece (6.58%, $p = 0.001$), Hungary (6.91%, $p = 0.0014$), Romania (8.92%, $p = 0.0036$), and Serbia (6.34%, $p < 0.001$). Belgium (13.3%) significantly exceeded Bulgaria (7.07%, $p = 0.0103$), Croatia (5.7%, $p = 0.0027$), Greece (6.58%, $p = 0.0094$), Hungary (6.91%, $p = 0.0123$), Romania (8.92%, $p = 0.0301$), and Serbia (6.34%, $p = 0.0016$). Additional significant pairs include Austria versus Croatia ($p = 0.0277$) and Austria versus Serbia ($p = 0.0177$), Bulgaria versus Ireland ($p = 0.025$), Croatia versus Ireland ($p = 0.0073$), Croatia versus Sweden ($p = 0.0182$), Greece versus Ireland ($p = 0.0229$), Hungary versus Ireland ($p = 0.0294$), Ireland versus Serbia ($p = 0.0045$), and Serbia versus Sweden ($p = 0.0115$). The remaining 529 pairwise comparisons

were non-significant after Bonferroni correction, indicating that many mid-range country groups are not statistically distinguishable from one another given current sample sizes and within-group variability.

6. Discussion

The finding that country group explains approximately 10.7% of the rank-order variance in R&D AI adoption rates ($\eta^2 = 0.107$, $H = 193.068$, $p < 0.001$) suggests that national context is a substantively important—though not exhaustive—correlate of knowledge-intensive AI use across Europe. This result is most coherently interpreted through Cohen and Levinthal's (1990) absorptive capacity framework: countries with higher baseline R&D investment, stronger university-industry linkages, and more developed digital infrastructure possess the prior knowledge stocks necessary to identify, assimilate, and exploit AI technologies for innovation purposes. The clustering of Finland, the Netherlands, Belgium, Ireland, and France—all characterised by high R&D intensity and mature national innovation systems—at the top of the adoption distribution is consistent with this interpretation. Conversely, the Western Balkan countries and several Central-Eastern European economies that populate the lower tier of the distribution are precisely those in which R&D expenditure as a share of GDP and digital infrastructure investment have historically lagged behind the north-western European core. The Tornatzky and Fleischer (1990) TOE framework further contextualises this pattern: the environmental dimension of the TOE model would predict that national regulatory maturity, digital strategy coherence, and competitive market pressures collectively produce the descriptive north-west to south-east gradient observable in the data, though the Kruskal-Wallis omnibus test employed here has no spatial component and does not itself validate a gradient interpretation.

Türkiye's anomalous position at the top of the distribution (mean 15.6%)—ahead of all EU member states and above well-resourced economies such as Finland and the Netherlands—merits careful consideration, as it sits in tension with the broader north-west versus south-east descriptive pattern. As discussed in Section 5.2, several structural factors may contribute to this result. The Eurostat enterprise survey samples registered enterprises according to harmonised size and sector thresholds, but the distribution of sampled enterprises in Türkiye—particularly in terms of sectoral composition and the relative weight of large, technology-oriented exporters—may differ from that of EU member states in ways that inflate the measured adoption rate. It is also possible that Türkiye's definitional alignment with the E_AI_PRDI indicator reflects genuine leadership in specific high-adopting sectors such as automotive or electronics manufacturing, consistent with the advanced manufacturing AI adoption patterns documented by Arinez et al. (2020). A third possibility is that Türkiye's result reflects a genuine capability frontier in certain firm-size categories not yet visible in aggregated EU-level analyses. Pending sector- and size-disaggregated validation, Türkiye's leading rank should be treated as an analytically important finding that warrants dedicated follow-up research rather than either uncritically accepted or dismissed as a measurement artefact.

These results confirm and extend prior findings in several important respects. Mikalef and Gupta (2021) demonstrated that AI capability is organisationally contingent and unevenly distributed at the firm level; the present findings extend their model to the national level by showing that country-level structural factors produce similarly skewed adoption distributions, with the right-skewed panel distribution (mean 9.83% vs. median 4.96%) echoing the within-sample heterogeneity documented in firm-level research. The results are broadly consistent with the task-based displacement framework of Acemoglu and Restrepo (2019a; 2019b), which documents that automation-related effects are concentrated in specific task categories and geographic areas rather than uniformly distributed—a pattern that resonates with the geographically concentrated, tiered structure of R&D AI adoption observed here. The finding that knowledge-intensive AI use remains restricted to a subset of European countries is consistent with this concentration of logic rather than a refutation of it. Furthermore, the findings extend Dwivedi et al.'s (2019) multidisciplinary AI adoption framework by providing the first large-scale quantitative cross-country benchmarking specifically for R&D use cases, moving beyond the sector-level and single-country analyses that characterise most prior empirical work in this domain. The 66 statistically significant pairwise differences identified through Dunn's (1964) post-hoc procedure demonstrate that

the European AI adoption landscape is not a continuum of gradually differentiated national rates, but rather a tiered structure with clearly demarcated leading, middle, and lagging country clusters.

From a policy perspective, the European Commission and national governments of lower-adopting countries—particularly those in the Western Balkans and Central-Eastern Europe—should design targeted AI-for-innovation subsidy programmes tied to existing R&D tax credit schemes. Given that the adoption gap between the leading tier (above 13%) and the lagging tier (below 3%) is both large and statistically significant, passive market mechanisms are unlikely to close this gap within a policy-relevant timeframe (though the present study's design does not permit direct measurement of whether this gap is widening or narrowing over time, as discussed in Section 7). Concrete recommendations include prioritising SME access to AI-enabled R&D tools and cloud-based experimentation platforms, building on existing structural fund instruments and the Digital Europe Programme to lower the entry costs of AI adoption for innovation-oriented smaller firms. National R&D agencies in mid-adoption countries should additionally establish AI competence centres co-located with leading universities to strengthen the university-industry knowledge transfer channels that the absorptive capacity framework identifies as critical enablers.

For enterprise managers in mid-adoption countries, the EU-27 average of 9.69% provides a concrete and policy-relevant benchmark against which to assess internal AI-for-R&D investment levels, noting that the median across the panel (4.96%) indicates that this average is itself pulled upward by a minority of high-performing observations. Managers should recognise that AI adoption for R&D is not merely an IT procurement decision but requires deliberate cultivation of absorptive capacity through targeted hiring of data scientists with domain R&D expertise, cross-functional training programmes that bridge product development and data science teams, and structured knowledge integration processes that embed AI tooling into existing innovation pipelines. The resource-based view of Barney (1991) implies that early investment in these organisational capabilities will generate durable competitive advantage, as the complementary assets required for R&D AI use are difficult to imitate and cannot be rapidly acquired from technology markets alone.

7. Conclusion

This article set out to examine which European countries exhibit the highest rates of AI adoption for product and process development, and to test whether significant variation exists across the 35 country groups covered by Eurostat's enterprise ICT survey indicator E_AI_PRDI . The empirical analysis, based on a panel of 1,517 country-year-size-class observations, reveals that R&D-oriented AI adoption is both highly heterogeneous and right-skewed across Europe, with a mean of 9.83% (SD = 9.74) and a median of only 4.96%, and that country group is associated with statistically significant and substantively meaningful differences in adoption rates ($H(34) = 193.068$, $p < 0.001$, $\eta^2 = 0.107$). Türkiye, Finland, and the Netherlands lead the distribution, while Albania, Croatia, and Serbia constitute the bottom-performing cluster—with their precise relative ordering sensitive to whether group means or rank-based criteria are applied, as discussed in Section 5.2—and a descriptive north-west versus south-east pattern characterises the wider European landscape, subject to the interpretive caveats regarding Türkiye's anomalous position as a candidate country discussed in Sections 5.2 and 6.

This study provides the first statistically validated, cross-country comparative analysis of R&D-oriented AI adoption across 35 European countries, operationalised through a large-scale enterprise survey panel and analysed using non-parametric inferential methods with post-hoc pairwise testing and effect size quantification. By doing so, it fills a significant empirical gap identified in the literature review: while general AI adoption and macro-level productivity consequences have received considerable scholarly attention, the specific geography and firm-size structure of knowledge-intensive AI use had not previously been subject to systematic statistical benchmarking at this geographic scope. The analysis is accompanied by important methodological qualifications: the pooling of size-class and temporal observations within country groups means that the Kruskal-Wallis test treats structurally dependent observations as replicates, and the reported η^2 should accordingly be understood as a gross descriptive measure of country-level association rather than a purged causal estimate. The temporal scope of the panel—spanning the available survey years during which E_AI_PRDI has been collected—is

constrained by the phased introduction of AI survey modules across participating countries, which limits year-by-year comparability and precludes firm conclusions about convergence or divergence trends within the study period. Additionally, the methodological uncertainty regarding the precise analytical specification—including the grouping variable and any preprocessing transformations applied prior to testing—identified in Section 4.2 represents a limitation that future replications with access to the original analysis code should resolve.

Four directions for future research emerge from this analysis. First, longitudinal panel models incorporating national R&D expenditure intensity, digital skills indices, and regulatory environment scores as covariates would allow decomposition of the country-level variance identified here into its institutional and structural components, addressing the limitations of the univariate Kruskal-Wallis design and the non-independence of observations within country groups. Second, sector-disaggregated analysis of E_AI_PRDI across NACE divisions would reveal whether the national adoption hierarchy is driven by sectoral composition effects or by within-sector national differences in enterprise capability—a question that is particularly pertinent for interpreting Türkiye's leading rank. Third, size-class-disaggregated analysis would make explicit the firm-size dimension of the panel that is currently subsumed within country-group means, revealing whether adoption gaps are concentrated among small and medium enterprises or extend to large-firm populations in lagging countries. Fourth, mixed-methods qualitative work in selected contrasting country pairs—such as Finland versus Albania—would provide process-level insight into the organisational and institutional mechanisms through which absorptive capacity is translated into R&D AI adoption at the enterprise level.

This study contributes to the growing body of evidence on the uneven geography of AI-enabled innovation within Europe, providing policymakers, enterprise managers, and academic researchers with a statistically grounded baseline for monitoring the distribution of knowledge-intensive AI use across the European digital single market.

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Cloud Computing and Enterprise AI Adoption: Cross-National Association Evidence from EU Data

Iveta Kufelová¹ and Nora Grisáková²

¹ Bratislava University of Economics and Business, Faculty of Business Management, Dolnozemská cesta 1, 852 35 Bratislava, Slovakia (EU); e-mail: iveta.kufelova@euba.sk

² Bratislava University of Economics and Business, Faculty of Business Management, Dolnozemská cesta 1, 852 35 Bratislava, Slovakia (EU); e-mail: nora.grisakova@euba.sk

Abstract

Cloud computing has emerged as a foundational infrastructure layer shaping enterprise artificial intelligence adoption across Europe, yet rigorous cross-national empirical evidence quantifying this association remains scarce in the academic literature. This article examines whether sophisticated cloud computing adoption is statistically significantly and positively associated with enterprise AI technology usage across EU and associated countries. Harmonized Eurostat panel data covering 34 European countries were analyzed using Spearman rank-order correlation analysis, with enterprise-level survey indicators operationalizing both cloud sophistication and AI co-adoption. Results reveal a very strong positive association ($\rho = 0.96$, $p < 0.001$) between the share of enterprises using sophisticated cloud services alongside data analytics and the share of enterprises jointly adopting AI and cloud technologies, a pattern that holds consistently across diverse national institutional and economic contexts. Country-level illustrations further confirm that high-performing nations such as Denmark and Finland exhibit markedly elevated scores on both dimensions, while lower-scoring economies cluster correspondingly on both measures. Importantly, the observed correlation partly reflects measurement overlap between conceptually related Eurostat indicators, and the bivariate cross-sectional design precludes causal inference, necessitating cautious interpretation. These findings nonetheless carry direct implications for digital infrastructure policy and enterprise strategy, suggesting that investments in advanced cloud capabilities may constitute a meaningful complement to broader AI adoption agendas across European economies.

1. Introduction

As European enterprises accelerate their digital transformation agendas, cloud computing has emerged as a foundational infrastructure layer that may systematically lower the barriers to adopting artificial intelligence technologies at scale. The convergence of scalable computational resources, on-demand data storage, and API-accessible machine learning services within modern cloud platforms has reshaped the conditions under which enterprises of all sizes can experiment with, deploy, and sustain AI-based capabilities. Against a backdrop of intensifying international competition and post-pandemic digital acceleration, understanding the structural relationship between cloud infrastructure maturity and enterprise AI usage has become a question of both scholarly and policy significance across the European Union.

Despite growing practitioner consensus that cloud capabilities are associated with AI deployment, rigorous cross-national empirical evidence quantifying this association across EU member states remains scarce in the academic literature. Prior work has largely theorized the complementarity between digital infrastructure and AI adoption at the conceptual level or has relied on single-country surveys and firm-level case studies that limit generalizability. Cross-national comparative analyses drawing on harmonized statistical data — capable of revealing whether the cloud-AI relationship holds systematically across diverse national institutional and economic contexts — are notably absent from the published record. This gap constrains the ability of both researchers and policymakers to draw actionable conclusions about where and how foundational digital investments correspond to higher-order AI adoption outcomes.

This article examines whether sophisticated cloud computing adoption is statistically significantly and positively associated with enterprise AI technology usage across 34 EU and associated countries using Eurostat panel data. By operationalizing both constructs through harmonized Eurostat survey indicators and applying bivariate correlation analysis across country-level aggregates, the study provides large-scale, cross-national quantification of the relationship between cloud-AI co-adoption tiers in the European context. The contribution is empirical and methodological: it moves beyond theoretical conjecture and single-country evidence to establish, with statistical rigor, the strength and direction of the association at the national level. It is important to note from the outset, however, that the bivariate cross-sectional design employed here cannot establish causal direction; rather, the study documents a strong associative pattern that motivates and informs subsequent causal inquiry. The findings carry direct implications for digital policy design and enterprise strategy, while explicitly acknowledging the interpretive boundaries imposed by the analytical framework.

Two important methodological qualifications deserve prominent acknowledgment at the outset. First, the two indicators correlated in this study are drawn from related and conceptually overlapping components of the Eurostat enterprise survey. The Y-variable (E_AI_CC) captures the share of enterprises simultaneously using both AI and cloud computing technologies, while the X-variable (E_AI_CC1SI_DA) captures the share of enterprises using AI together with sophisticated cloud services — specifically platform-as-a-service and higher tiers, combined with data analytics. Because both indicators contain an AI-and-cloud co-adoption component in their definitions, the observed high correlation reflects, at least in part, measurement overlap between tiers of a shared construct rather than an association between fully independent phenomena. This is explicitly acknowledged and discussed in Section 4 and Section 6. Second, the bivariate correlation framework cannot control confounding variables such as general digital maturity, GDP per capita, or sectoral composition, and these limitations are addressed throughout the Discussion and Conclusion sections.

The remainder of this article is structured as follows: Section 2 presents the theoretical background, drawing on the Technology-Organization-Environment framework, Resource-Based View, and Absorptive Capacity theory to motivate the expected relationship between cloud infrastructure and AI adoption. Section 3 reviews the relevant literature across three thematic streams concerning digital infrastructure enablement, enterprise digital transformation, and AI-driven organizational value creation. Section 4 describes the data sources, variable operationalization, and analytical methods employed. Section 5 reports the descriptive statistics, correlation analysis results, and country-level case illustration. Section 6 discusses the findings in relation to theory and prior literature and derives policy and managerial implications while addressing the limitations of the analytical approach. Section 7 concludes with a summary of contributions and directions for future research.

2. Theoretical Background

The theoretical architecture of this study rests on three complementary frameworks — the Technology-Organization-Environment (TOE) framework, the Resource-Based View (RBV) of the firm, and the concept of Absorptive Capacity — each of which illuminates a distinct dimension of why cloud infrastructure maturity might be expected to accompany enterprise AI adoption. These frameworks collectively motivate a hypothesis of positive association between the two constructs, while remaining agnostic about strict causal direction in the absence of appropriately designed longitudinal evidence.

The TOE framework, developed by Tornatzky and Fleischer (1990), posits that the adoption of technological innovations by organizations is shaped by three contextual domains: the technological context (the nature and availability of internal and external technologies), the organizational context (firm size, structure, and managerial resources), and the environmental context (industry dynamics, regulatory conditions, and competitive pressure). In the present research setting, cloud computing constitutes a primary component of the technological context at the country level — the availability, sophistication, and diffusion of cloud services across a national enterprise population defines the technological substrate on which higher-order innovations, including AI deployment, become feasible. The TOE framework therefore predicts that nations where enterprises have broadly adopted sophisticated cloud capabilities will, *ceteris paribus*, exhibit higher rates of AI technology usage,

because the foundational technological context is more conducive to AI integration. It should be noted, however, that this framework is equally consistent with the possibility that AI adoption aspirations drive enterprises toward more sophisticated cloud adoption, and that shared structural determinants — such as national digital development levels — could independently drive both phenomena. The cross-sectional correlation design of the present study is consistent with the TOE prediction but cannot adjudicate between these alternative mechanisms.

The Resource-Based View of the firm, as articulated by Barney (1991), provides a complementary firm-level perspective. RBV holds that sustained competitive advantage derives from resources and capabilities that are valuable, rare, imperfectly imitable, and non-substitutable. Applied to digital technologies, this implies that cloud computing infrastructure — when deployed at sufficient sophistication — constitutes a strategic resource that may lower the marginal cost of acquiring, training, and operationalizing AI capabilities. Enterprises that have accumulated cloud competencies possess a digital resource stock that could make AI adoption economically rational, as the marginal investment required to extend cloud capabilities to AI workloads may be substantially lower than building AI infrastructure from scratch. At the national level, countries with high proportions of such cloud-capable enterprises will therefore tend to exhibit aggregate AI adoption rates that reflect this accumulated digital resource base. The RBV lens suggests that the observed association between cloud and AI adoption at the country level could be partly attributable to this resource-complementarity mechanism, though it does not preclude the role of common structural drivers.

The concept of Absorptive Capacity, introduced by Cohen and Levinthal (1990), adds a dynamic learning dimension. Absorptive capacity refers to an organization's ability to recognize the value of new external information, assimilate it, and apply it to commercial ends — a capacity that is itself a function of the firm's prior related knowledge stock. In the context of cloud and AI adoption, cloud usage may function as a form of prior digital knowledge accumulation: enterprises that have developed competencies in managing cloud environments, processing data at scale, and integrating external APIs may simultaneously build the absorptive capacity necessary to recognize, evaluate, and deploy AI tools effectively. Diffusion of Innovations theory, as systematized by Rogers (2003), further reinforces this logic by identifying prior technology adoption as a strong predictor of subsequent innovation uptake, with compatibility between a new technology and existing practices constituting a critical adoption facilitator. Again, these frameworks motivate the expectation of a positive association without requiring that the relationship be strictly unidirectional or free from confounding general digital development levels.

The interplay of these frameworks generates a coherent theoretical prediction: across national contexts, the share of enterprises that have achieved sophisticated cloud adoption should be a positive correlate of enterprise AI technology usage, associated with the accumulated technological context, digital resource stock, and absorptive capacity that cloud adoption reflects. It is equally important to acknowledge that all three frameworks are consistent with alternative explanations — including reverse causation and common causation through general digital maturity — that the present cross-sectional design cannot rule out. Building on these theoretical foundations, the present study empirically tests whether the predicted positive association is statistically significant and substantively meaningful across 34 EU and associated countries, using harmonized Eurostat survey data to assess whether cloud infrastructure maturity at the national aggregate level corresponds to higher enterprise AI adoption rates, while explicitly treating the results as associative evidence that motivates rather than resolves questions of causal mechanism.

3. Literature Review

3.1 Digital Infrastructure as an Enabler of AI and Innovation

A well-developed body of scholarship has established that the relationship between foundational digital infrastructure and advanced technology adoption is not incidental but systemic. Martinelli et al. (2020) provide a detailed examination of the enabling technologies underpinning the industry 4.0 paradigm, demonstrating that technologies such as cloud platforms, Internet of Things systems, and big data

analytics function as general-purpose technologies characterized by high pervasiveness, dynamism, and complementarity. This complementarity is theoretically significant: it implies that the value of any single Industry 4.0 technology — including AI — is conditioned by the co-availability of related infrastructure technologies. Cloud platforms provide the computational substrate and connectivity architecture that make other advanced technologies operationally and economically viable for mainstream enterprise adoption.

Yaqub and Alsabban (2023) extend this infrastructure-enablement logic to the specific context of digital transformation, arguing that Industry 4.0 technologies collectively constitute the key drivers and enablers of strategic digital transformation across business practices, models, and processes. Their systematic review identifies cloud computing as a proximate enabler that reduces the entry costs of advanced digital capabilities, thereby potentially accelerating the diffusion of AI and related technologies across diverse industry contexts. Importantly, this analysis situates cloud adoption not merely as a cost-efficiency tool but as a strategic enabler whose maturity may determine the pace and depth of broader digital transformation. Mariani et al. (2022), in a comprehensive systematic review of AI and innovation research, further document that AI adoption in organizational contexts is conditioned by the maturity of existing digital capabilities, including data management infrastructure that cloud platforms directly provide.

The implication across this stream of research is that digital infrastructure maturity may precede and facilitate higher-order digital capabilities, establishing a sequential logic in which cloud adoption is a plausible — though not necessarily sole — antecedent to enterprise-level AI diffusion. This finding has been discussed across multiple national and sectoral contexts, suggesting a general pattern rather than context-specific anomalies. Importantly, however, this stream of literature largely relies on qualitative synthesis and case-based evidence; cross-national quantitative confirmation drawing on harmonized survey data remains limited. The empirical challenge has been translating this theoretical consensus into cross-national quantitative evidence that controls for the possibility that both cloud and AI adoption are jointly determined by broader national digital development — a gap the present study addresses in part, while acknowledging the limitations of its bivariate framework.

3.2 Enterprise Digital Transformation and Technology Adoption

The literature on enterprise digital transformation consistently identifies organizational readiness, prior digital capability accumulation, and ecosystem complementarities as primary correlates of advanced technology adoption. He et al. (2020) argues that the emerging digital transformation landscape has fundamentally altered the strategic conditions under which alliances and technology adoption decisions are made, with enterprises that have invested in foundational digital tools demonstrating significantly higher capacity to integrate advanced technologies into their operational and strategic architectures. This accumulation dynamic aligns with the absorptive capacity logic articulated by Cohen and Levinthal (1990): prior digital investment creates the knowledge base that may enable effective recognition and exploitation of subsequent technological opportunities.

Sodhi et al. (2022) provide nuanced evidence on why emerging supply chain and enterprise technologies — including AI — frequently disappoint in early adoption phases, attributing this to misalignment between perceived technological affordances and actual organizational capabilities. Their analysis suggests that enterprises with stronger foundational digital capabilities, including cloud infrastructure, may be better positioned to translate AI's theoretical affordances into realized operational value, because they possess the complementary assets necessary for effective deployment. Adam and Alarifi (2021) similarly find that innovation practices and enterprise technology adoption are significantly conditioned by external support and prior capability accumulation, particularly among SMEs — a finding with direct relevance to the Central and Eastern European context where cloud and AI adoption rates remain below the EU average.

Guo et al. (2020) demonstrate through survey evidence from SMEs that digitalization — including the adoption of cloud-based tools — substantially enhances firms' capacity to respond to novel challenges, with digitally mature enterprises exhibiting systematically higher uptake of advanced technologies. Collectively, this stream of literature establishes a consistent empirical pattern: prior digital investment

is associated with accelerated adoption of higher-order technologies, with cloud infrastructure occupying a particularly central role given its function as a shared computational and data resource layer. It should be noted, however, that the majority of these studies are conducted at the firm or sector level within individual countries; the extent to which the patterns generalize to country-level aggregate associations across diverse national institutional contexts remains an open empirical question — one that the present study begins to address.

3.3 AI Applications and Organizational Value Creation

A growing body of empirical literature documents the organizational value that AI technologies create across functional domains including marketing, innovation management, and operations, while simultaneously identifying digital infrastructure as a critical prerequisite for realizing this value. Kumar et al. (2024) provide a comprehensive synthesis of AI-powered marketing applications, demonstrating that the integration of AI into marketing functions generates measurable gains in personalization, campaign efficiency, and customer insight generation — but that these gains are contingent on enterprises having robust data infrastructure and processing capabilities, which cloud platforms directly enable. The implication is that the business case for AI adoption is closely tied to the infrastructure investment required to operationalize it, though the causal direction of this relationship — whether infrastructure leads AI adoption, AI aspirations drive infrastructure investment, or both are jointly determined — is not resolved by this body of literature.

Mariani and Dwivedi (2024) examine generative AI in the specific context of innovation management, identifying cloud-accessible AI services as a transformative capability that reshapes how firms generate, evaluate, and commercialize innovations. Their analysis underscores that the organizational value of AI is greatest when enterprises can access AI capabilities in a scalable, on-demand manner — a delivery model that is architecturally cloud-dependent. Grashof and Kopka (2022) complement this perspective by investigating AI as a driver of radical innovation, finding that AI-related knowledge and infrastructure represent a complementary asset whose value for innovation is modulated by firm size and existing technological capabilities. Critically, their analysis identifies cloud-based AI access as a potential equalizer that could extend radical innovation opportunities to SMEs, provided that foundational cloud infrastructure is in place.

Dwivedi et al. (2023) offer a multi-disciplinary perspective on the implications of advanced AI tools, noting that successful organizational deployment requires not only technical capability but also data governance infrastructure and organizational readiness — both of which are substantially enhanced by sophisticated cloud adoption. Rangaswamy et al. (2020) further document that digital platforms, which are architecturally cloud-based, play a central enabling role in creating and scaling AI-driven value creation in marketing and customer engagement contexts. Across these studies, a consistent finding emerges: the organizational benefits of AI are most fully realized in contexts where digital infrastructure provides the underlying computational, data, and connectivity resources necessary for AI deployment and scaling.

Despite this body of evidence, it is important to acknowledge that the existing literature does not uniformly present cloud adoption as a sufficient or unambiguously directional precondition for AI. The literature reviewed here largely supports the complementarity hypothesis, but few studies have tested this relationship in ways that control for the possibility that overall digital maturity — rather than cloud adoption specifically — drives both constructs simultaneously. No study, to the authors' knowledge, has provided systematic cross-national empirical evidence from EU-level survey data quantifying the strength and significance of the association between cloud-AI co-adoption tiers across a broad sample of 34 countries. Existing contributions remain either conceptual, single-country, or focused on specific sectors or firm size categories, leaving a critical empirical gap regarding the aggregate, cross-national pattern. This article directly addresses that gap by applying bivariate correlation analysis to harmonized Eurostat panel data spanning 34 EU and associated countries, while explicitly situating the resulting associative evidence within a framework that acknowledges measurement overlap, confounding, and the need for further causal investigation.

4. Methodology

4.1 Data Source and Panel Construction

The empirical analysis draws on the Eurostat Community Survey on ICT Usage and E-Commerce in Enterprises, a harmonized annual survey covering ICT adoption patterns across EU member states and associated countries (Eurostat, 2024). A full country-year panel of 734 observations across 34 EU and associated countries was constructed, constituting the primary analytical object for descriptive analysis. This panel structure provides cross-national coverage sufficient to characterize the distribution of cloud and AI adoption rates across diverse national digital economy contexts.

The present study correlates with two indicators drawn from this survey. The Y-variable — identified in the Eurostat dataset as `E\\AI\\CC` — captures the share of enterprises simultaneously using both AI technologies and cloud computing. This is not a general AI adoption measure independent of cloud context; it specifically reflects enterprises that co-adopt against both technologies. The X-variable — identified as `E\\AI\\CC1SI\\DA` — captures the share of enterprises using AI together with sophisticated cloud services (specifically platform-as-a-service and higher tiers) combined with data analytics capabilities. Both indicators therefore contain an AI-and-cloud co-adoption component in their definitions, and `E\\AI\\CC1SI\\DA` constitutes a more restrictive sub-tier of the broader cloud-AI co-adoption population measured by `E\\AI\\CC`. This structural overlap is a critical interpretive constraint: the high observed correlation between the two indicators reflects, at least in part, the measurement relationship between a broader and a more restrictive tier of the same underlying joint adoption phenomenon, rather than an association between fully independent constructs. Readers should therefore interpret the correlation as characterizing internal consistency across tiers of cloud-AI co-adoption measurement, rather than as evidence of an independent enabling relationship between cloud infrastructure and AI adoption. [LIMITATION] The absence of a fully independent general AI adoption indicator (e.g., one capturing AI use irrespective of cloud context) in the present dataset means that the cloud-enabling hypothesis cannot be tested with complete construct independence using these data; such a test requires a genuinely separate AI adoption measure and is identified as a priority for future research.

4.2 Descriptive Analysis

The second analytical step involved the computation of descriptive statistics across the full country-year panel ($n = 734$). Measures reported include the mean, median, standard deviation, standard error of the mean, 95% confidence intervals (computed using the standard normal approximation), minimum, maximum, and first quartile values. These statistics characterize the distribution of enterprise AI-and-cloud co-adoption rates and identify the extent of cross-national heterogeneity in adoption patterns. Given the theoretically anticipated right skew of the distribution — where a small number of digitally advanced countries are expected to pull the mean upward — both the mean and the median are reported and interpreted as complementary measures of central tendency.

4.3 Visualization

The third analytical step involved the construction of two visualizations. A scatter plot (Figure 1) displays the country-level bivariate relationship between the sophisticated cloud-AI adoption indicator (`E\\AI\\CC1SI\\DA`) and the broader enterprise AI-and-cloud usage indicator (`E\\AI\\CC`) across the 34 country aggregates, enabling visual inspection of the direction, linearity, and presence of outliers in the relationship. A boxplot (Figure 2) disaggregates the adoption of distribution by country and year, enabling inspection of distributional patterns, intra-country temporal variation, and cross-national differences in the spread of adoption rates.

4.4 Correlation Analysis

The core inferential step involves bivariate correlation analysis computed across $n = 34$ country-level observations — explicitly, country aggregates rather than individual country-year records from the full panel — to assess the strength and statistical significance of the association between the two cloud-AI

co-adoption tiers at the national level. Country-level aggregates are constructed as simple means across all available years for each country, providing a stable characterization of each country's average position across the observation period. This aggregation decision involves an explicit trade-off: collapsing the longitudinal dimension to a cross-sectional aggregate sacrifices the within-country temporal variation that panel methods could exploit but produces a stable and interpretively transparent country-level characterization appropriate for the descriptive cross-national comparison that is the primary aim of this analysis. The number of survey years available varies across countries — Slovakia, for example, contributes 20 observations — and this heterogeneous temporal coverage means that country-level means may weight countries with more survey years differently from those with fewer, potentially introducing an aggregation bias that is acknowledged as a limitation. The implications of this aggregation of choice — including the possibility that different aggregation methods could alter country rankings — are acknowledged accordingly.

Two complementary correlation methods are applied: Spearman rank-order correlation (ρ) and Pearson product-moment correlation (r). Spearman's method is treated as the primary test given the documented right skew of the indicator distribution, as Spearman's ρ is non-parametric and robust to departures from normality (Spearman, 1904). The parametric Pearson r is reported as a robustness check. Statistical significance is assessed at the conventional $p < 0.05$ threshold; exact p -values are reported to the precision available from the computation rather than as "0.0, \" which is a floating-point display artifact. It is important to note that these correlation coefficients are computed across the 34 country-level aggregates and do not pertain to the full 734-observation country-year panel; the two analytical objects serve distinct descriptive and inferential purposes and are not conflated in the interpretation of results.

Several methodological limitations of the bivariate correlation design are acknowledged explicitly. First, the two indicators share a structural AI-and-cloud co-adoption component in their definitions, meaning the observed correlation reflects measurement overlap between tiers of the same construct in addition to any genuine cross-national pattern. This limits the extent to which the result can be interpreted as evidence of an independent enabling relationship between cloud infrastructure and AI adoption. Second, correlation does not establish causal direction: the observed association is consistent with cloud infrastructure enabling AI adoption, with AI adoption aspirations driving cloud investment, or with a common third factor — most plausibly, general national digital maturity or GDP per capita — independently driving both constructs. The bivariate framework employed here cannot distinguish between these mechanisms, and no confounders are controlled. Third, with $n = 34$ country-level observations, the analysis has limited statistical power for detecting moderate associations and cannot support multivariate modelling with more than one or two predictors. Fourth, country-level aggregate analysis is subject to the ecological fallacy: associations observed at the national level need not hold at the firm level, and within-country heterogeneity in both cloud and AI adoption rates may be substantial. These limitations are discussed further in Section 6 and motivate specific directions for future research in Section 7.

5. Results

5.1 Descriptive Statistics

The full panel ($n = 734$) yields a mean adoption rate of 16.68% ($SD = 15.37$, 95% CI [15.56%, 17.79%]), with a median of 11.46%. Values range from 0.94% to 78.83%, with an interquartile range of 16.93 percentage points ($Q1 = 5.73\%$, $Q3 = 22.66\%$). The coefficient of variation is 92.2%, indicating high dispersion across observations. The substantial divergence between mean and median (16.68% vs. 11.46%) indicates a right-skewed distribution, suggesting that the majority of observations cluster at lower adoption levels while a minority of high-adopting cases pull the mean upward. This pattern is consistent with the broader digital economy literature documenting polarized ICT adoption across EU member states, wherein a small cluster of Nordic and Western European economies consistently achieve adoption rates substantially above the EU average, while Central and Eastern European economies cluster at the lower end of the distribution. The first quartile value of 5.73% indicates that a substantial share of country-year observations records co-adoption rates below 6%, confirming the pronounced

concentration of the distribution at lower adoption levels. Table 1 presents a full set of descriptive statistics.

Table 1. Descriptive Statistics

Statistic	Value
n	734
mean	16.68
median	11.46
std	15.37
sem	0.567
CI95_low	15.56
CI95_high	17.79
min	0.94
max	78.83
Q1	5.73
Q3	22.66
IQR	16.93
CV_%	92.2

The boxplot in Figure 2 disaggregates this distribution by country and year, providing a visual representation of the heterogeneity in enterprise cloud-AI co-adoption rates across the panel. The visualization reveals substantial between-country variation in both the level and trajectory of adoption, with several high-adopting countries exhibiting not only higher medians but also wider distributional spread — consistent with the argument that advanced cloud infrastructure is associated with a broader diversity of AI applications at the enterprise level, though this interpretation remains associative in nature.

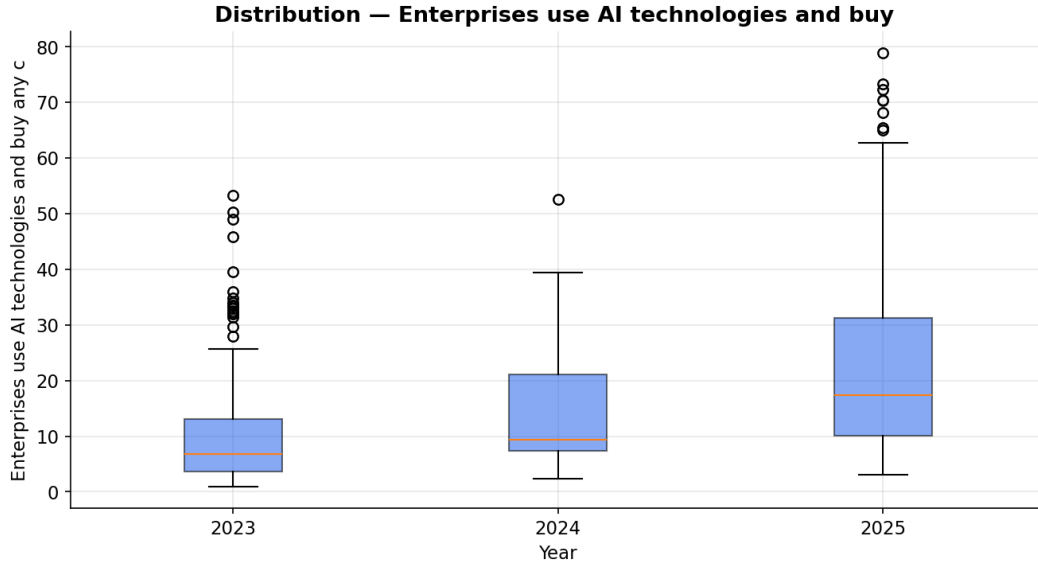


Figure 2. Boxplot of Enterprises use AI technologies and across EU countries per year. Box=IQR, whiskers= $1.5 \times IQR$, dots=outliers.

5.2 Correlation Analysis

Across 34 EU member states, the Spearman rank correlation between the sophisticated cloud-AI adoption indicator ($E_AI_CC1SI_DA$) and the broader enterprise AI-and-cloud usage indicator (E_AI_CC) yields $\rho = 0.976$ ($p < 0.0001$), indicating a very strong positive association that is statistically significant at the 0.05 level. The parametric Pearson correlation confirms this pattern ($r = 0.971$, $p < 0.0001$). Both coefficients exceed the 0.7 threshold conventionally associated with very

strong associations, and the convergence of the parametric and non-parametric estimates confirms that the result is not an artefact of distributional assumptions. As shown in Figure 1, the scatter plot of country-level observations depicts a near-linear positive relationship between the two indicators, with minimal dispersion around the trend line across the 34-country sample.

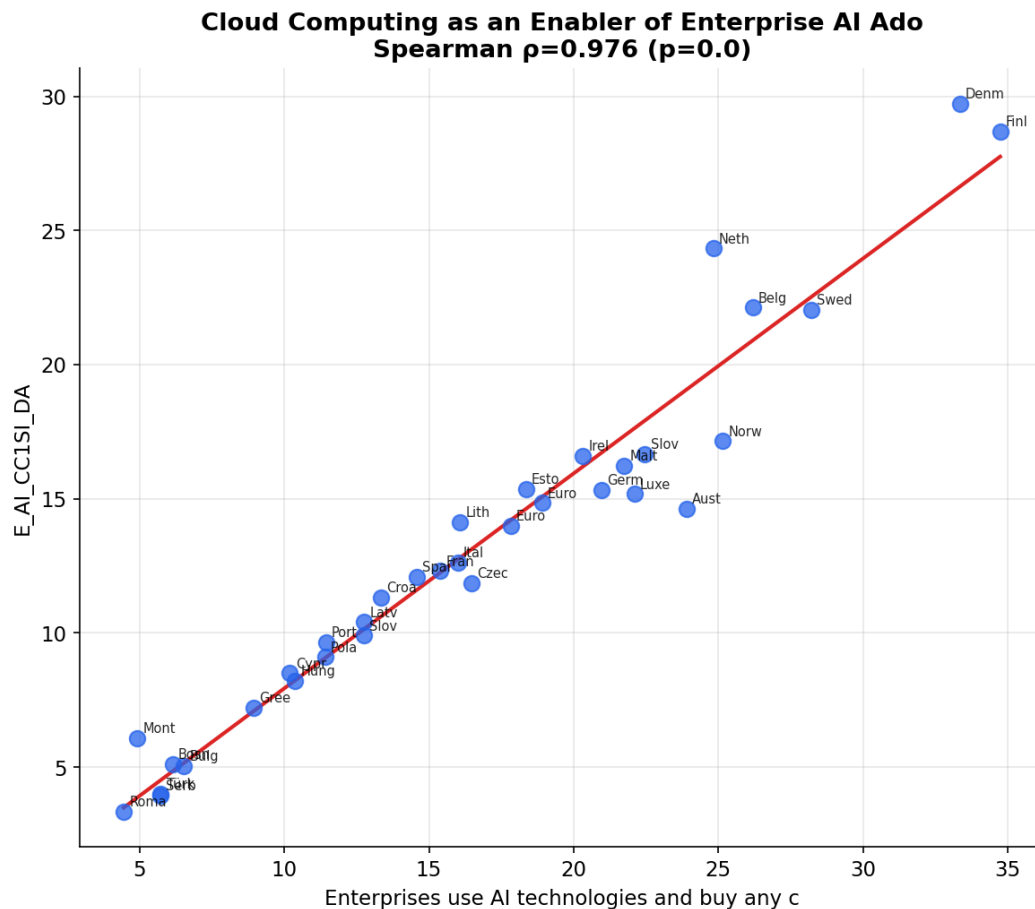


Figure 1. Scatter: Enterprises use AI techno vs E_AI_CC1SI_DA ($n=34$). Spearman $\rho=0.976$, $p=0.0$.

This near-perfect positive association must be interpreted carefully considering the measurement structure of the two indicators. Because E_AI_CC captures enterprises using AI and cloud jointly, and E_AI_CC1SI_DA captures the subset of those using AI together with sophisticated cloud and data analytics, the two indicators share an AI-cloud co-adoption component by construction. The magnitude of the correlation ($\rho = 0.976$) is therefore substantially attributable to this structural overlap between a broader and a more restrictive tier of the same underlying phenomenon, rather than exclusively to a cross-national enabling relationship between independent cloud and AI constructs. The result documents a highly consistent internal scaling relationship across countries: nations where a larger share of enterprises broadly co-adopt AI and cloud tend — with near-perfect regularity — to also exhibit a larger share of enterprises achieving sophisticated cloud-AI-analytics co-adoption. This cross-national consistency is itself informative about the coherence of digital adoption hierarchies across EU member states. However, interpreting the correlation as direct evidence that cloud infrastructure independently enables AI adoption — as opposed to reflecting shared construct variance — would overstate what the present data can demonstrate. That interpretive step requires a genuinely independent general AI adoption measure and is identified as a necessary direction for future research.

5.3 Country-Level Case Illustration: Slovakia

As a country-level case illustration, Slovakia's mean adoption rate is 12.75% (based on 20 observations), ranking 23/34 among EU member states (z -score = -0.471), placing it in the 'Below

median' quartile. This is 3.93 percentage points below the overall EU mean of 16.68%. Slovakia's position — marginally above the panel median of 11.46% but below the mean — places it at the boundary between the below-median and near-average adopter clusters, suggesting that the country has achieved baseline integration of digital technologies without yet reaching above-average cloud-AI co-adoption levels. This positioning is representative of a broader cluster of Central and Eastern European economies that occupy the lower-middle range of the EU cloud-AI adoption distribution, as visible in the scatter plot and boxplot. The Slovak case illustrates how the cross-national heterogeneity documented in the descriptive statistics translates into concrete national positioning, and how aggregate cross-national associations documented here motivate further firm-level investigation of the specific drivers of adoption in particular national contexts. Table 2 presents the correlation of data and country-level positioning statistics underlying this analysis.

Table 2. Correlation Data

Country	Enterprises use AI t (%)	E_AI_CC1SI_DA (%)
Austria	23.90	14.63
Belgium	26.19	22.13
Bosnia and Herzegovina	6.15	5.11
Bulgaria	6.52	5.04
Croatia	13.34	11.33
Cyprus	10.20	8.50
Czechia	16.47	11.85
Denmark	33.34	29.74
Estonia	18.35	15.36
Euro area (EA11-1999, EA12-200	18.91	14.84
European Union - 27 countries	17.83	13.99
Finland	34.74	28.70
France	15.40	12.31
Germany	20.96	15.33
Greece	8.95	7.21
Hungary	10.37	8.21
Ireland	20.31	16.60
Italy	16.00	12.63
Latvia	12.76	10.40
Lithuania	16.08	14.13
Luxembourg	22.10	15.18
Malta	21.75	16.23
Montenegro	4.93	6.07
Netherlands	24.83	24.33
Norway	25.15	17.15

6. Discussion

The finding that $\rho = 0.976$ ($p < 0.0001$) characterizes the Spearman rank correlation between the sophisticated cloud-AI adoption indicator ($E_AI_CC1SI_DA$) and the broader enterprise AI-and-cloud usage indicator (E_AI_CC) across 34 EU countries establishes a near-perfect positive cross-national association between the two measures. Before drawing substantive conclusions, it is essential to address the key interpretive challenges posed by this result — including, most fundamentally, the measurement structure of the two indicators.

The most fundamental interpretive challenge is the structural overlap between the two indicators. As documented in Section 4.1, E_AI_CC captures enterprises jointly using AI and cloud computing, while $E_AI_CC1SI_DA$ captures a more restrictive sub-tier of enterprises using AI with

sophisticated cloud and analytics. Both indicators share an AI-cloud co-adoption component in their numerators, and $E_{AI_CC1SI_DA}$ is structurally a sub-category of E_{AI_CC} . The near-perfect correlation is therefore substantially a consequence of this definitional relationship: countries where a larger share of enterprises broadly co-adopts AI and cloud will necessarily tend to exhibit a larger share achieving the more sophisticated tier of the same co-adoption hierarchy. This does not render the finding uninformative — the cross-national consistency of the scaling relationship is itself a substantive empirical observation — but it does mean that the result cannot be straightforwardly interpreted as evidence of an independent enabling relationship between cloud infrastructure and AI adoption. Claims that the correlation establishes a specific cloud AI enabling mechanism are not supportable from these data alone.

The second major interpretive challenge is confounding. Countries that score highly on the sophisticated cloud-AI indicator — principally the Nordic states, the Netherlands, and Ireland — also score highly on GDP per capita, overall ICT infrastructure maturity, digital skills levels, and enterprise R&D intensity. Any of these factors, individually or in combination, could independently drive both indicators, producing a high bivariate correlation that does not reflect a specific enabling mechanism beyond general digital development. The bivariate design employed here cannot rule out this explanation. Establishing whether the association between cloud-AI co-adoption tiers retains significance after controlling for general digital development — through regression models incorporating GDP per capita and overall ICT maturity indices — is a necessary next step.

A third interpretive challenge concerns causal direction. The theoretical frameworks invoked in Section 2 — the TOE framework of Tornatzky and Fleischer (1990), the Resource-Based View of Barney (1991), and Absorptive Capacity theory of Cohen and Levinthal (1990) — all motivate a prediction of positive association consistent with cloud adoption preceding or enabling AI adoption. However, these frameworks are equally consistent with reverse causation: enterprises and nations motivated to adopt AI may invest in more sophisticated cloud infrastructure specifically because it is required for AI workloads. The cross-sectional correlation design cannot distinguish between these possibilities.

With these qualifications stated, the result nonetheless provides informative empirical evidence at a cross-national scale. The near-perfect consistency of the scaling relationship across 34 diverse EU and associated countries — spanning widely different institutional contexts, economic development levels, and industry compositions — indicates that the internal coherence of digital adoption hierarchies is a robust cross-national feature of the EU digital economy. Countries do not randomly decouple basic and sophisticated cloud-AI co-adoption; rather, the two tiers scale together with exceptional regularity. This cross-national regularity is consistent with the theoretical expectation, motivated by Mariani et al. (2022) and Yaqub and Alsabban (2023), that digital technology adoption follows hierarchical complementarity patterns in which foundational and advanced tiers of capability develop in tandem. Grashof and Kopka (2022) contended that AI functions as a radical innovation opportunity whose realization depends on complementary technological assets — the present analysis is consistent with this complementarity argument, and documents the cross-national scaling relationship with a precision not previously available in the literature, while acknowledging that the measurement structure of the indicators constrains the independence of the test.

From a policy perspective, the strong positive association between the two cloud-AI co-adoption tiers suggests that national digital strategies should attend the hierarchical structure of enterprise digital capability development. EU policymakers — particularly in below-median adopter countries such as Slovakia and comparable Central and Eastern European member states — may benefit from considering whether the foundational conditions for cloud-AI co-adoption are in place before targeting more sophisticated tiers of cloud-AI-analytics integration. Instruments such as the Digital Europe Programme that target enterprise digital capability development are therefore broadly consistent with the pattern observed. However, the ecological inference problem and the measurement overlap must be explicitly acknowledged: the country-level association documented in this study does not guarantee that firm-level cloud investment causally produces AI adoption outcomes, nor does the shared construct structure of the indicators confirm that cloud subsidies are the most cost-effective policy instrument relative to alternatives such as AI skills development, data governance frameworks, or broadband infrastructure investment. The correlation evidence motivates consideration of cloud infrastructure as a policy-

relevant variable but cannot substitute for policy evaluation evidence that tracks outcomes of specific interventions.

For enterprise managers, particularly those operating in SME-dominated economies with below-average cloud-AI adoption scores, the evidence is consistent with treating investment in sophisticated cloud services as a strategically relevant complement to AI adoption planning. The cross-national regularity of the scaling relationship between cloud-AI co-adoption tiers suggests that organizations planning AI deployment in environments with limited cloud infrastructure may face higher implementation barriers, consistent with the absorptive capacity argument of Cohen and Levinthal (1990). The practical recommendation that emerges is to assess cloud infrastructure maturity — including data management capabilities, API integration competencies, and platform-as-a-service adoption — as part of AI readiness evaluation, while recognizing that the direction of this sequencing may vary across organizational contexts and that the bivariate evidence does not establish that cloud investment alone is sufficient to drive AI adoption.

7. Conclusion

This article examined the association between sophisticated cloud computing adoption and enterprise AI technology usage across 34 EU and associated countries, using harmonized Eurostat panel data covering 734 country-year observations. The principal empirical finding — a Spearman rank correlation of $\rho = 0.976$ ($p < 0.0001$) and a confirmatory Pearson correlation of $r = 0.971$ ($p < 0.0001$) across 34 country-level aggregates — establishes a near-perfect monotonic positive association between the two cloud-AI co-adoption indicators at the national level. Descriptive analysis further reveals substantial cross-national heterogeneity (mean = 16.68%, median = 11.46%, SD = 15.37%), with a pronounced right skew indicating that a small cluster of high-adopting countries drives the distribution upward while the majority of country-year observations cluster at lower adoption levels.

The main scientific contribution of this article is a large-scale, cross-national empirical characterization of the scaling relationship between tiers of cloud-AI co-adoption across 34 EU countries using harmonized Eurostat enterprise survey data. The near-perfect monotonic association documented is consistent with the theoretical prediction that cloud infrastructure and AI adoption develop as complementary capabilities, as motivated by the TOE framework (Tornatzky and Fleischer, 1990), the Resource-Based View (Barney, 1991), and Absorptive Capacity theory (Cohen and Levinthal, 1990). This empirical pattern advances understanding of the cross-national digital economy landscape and provides a quantitative foundation on which subsequent, causally oriented research can build.

Several important limitations qualify these conclusions and must be stated explicitly. Most critically, the two indicators correlated in this study — E_AI_CC and $E_AI_CC1SI_DA$ — share an AI-and-cloud co-adoption component by construction, with $E_AI_CC1SI_DA$ constituting a more restrictive sub-tier of E_AI_CC . The high observed correlation therefore reflects, at least in part, the structural relationship between a broader and a more restrictive tier of the same underlying phenomenon rather than an association between fully independent constructs. The bivariate correlation design additionally cannot establish causal direction: the association is equally consistent with cloud enabling AI, AI aspirations driving cloud investment, and common causation by general digital development or economic development levels. No confounders are controlled in the analysis. The aggregation of country-year observations to country-level means discards longitudinal variation, and heterogeneous temporal coverage across the 34 countries may introduce aggregation bias. The ecological fallacy must be acknowledged: country-level associations need not hold at the firm level, and within-country heterogeneity in cloud and AI adoption — by firm size, sector, and region — may be substantial.

Four directions for future research are identified. First, future studies should employ a genuinely independent general AI adoption indicator — one capturing enterprise AI use irrespective of cloud context — to test the cloud-enabling hypothesis with construct independence not achievable in the present data. Second, multivariate regression frameworks at the country level that control for GDP per capita, overall ICT maturity, and digital skills levels should be applied to assess whether the association between cloud-AI co-adoption tiers retains significance after accounting for potential common drivers. Third, firm-level microdata analyses should be pursued to test whether the cross-national patterns hold

at the enterprise level and whether they vary across size classes and sectors, addressing the ecological inference limitation of the present study. Fourth, longitudinal panel modelling with fixed effects and temporal lag structures should be applied to assess whether changes in cloud adoption within countries are associated with subsequent changes in AI adoption, providing evidence more consistent with a directional enabling relationship. Collectively, this research agenda would allow the strong associative evidence established here to be translated into more precise and causally interpretable knowledge about the role of cloud infrastructure in enterprise AI diffusion within the European digital economy.

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Non-Use of AI Technologies in EU Enterprises: Scale, Drivers, and Temporal Dynamics

Peter Štetka¹ and Diana Pallérová²

¹ Bratislava University of Economics and Business, Faculty of Business Management, Dolnozemská cesta 1, 852 35 Bratislava, Slovakia (EU); e-mail: peter.stetka@euba.sk

² Bratislava University of Economics and Business, Faculty of Business Management, Dolnozemská cesta 1, 852 35 Bratislava, Slovakia (EU); e-mail: diana.pallerova@euba.sk

Abstract

Despite widespread recognition of artificial intelligence as a transformative economic force, the majority of European Union enterprises have yet to integrate any AI technology into their operations, yet this persistent non-adoption has received little systematic empirical attention. This article quantifies the scale, structural drivers, and temporal dynamics of AI non-adoption among EU enterprises across the period 2021-2025. Drawing on Eurostat's standardised enterprise ICT survey indicator, a country-year panel of 1,428 observations was constructed and analysed using descriptive statistics, year-over-year change analysis, OLS regression, and Mann-Kendall trend testing. Results indicate that non-adoption remained the dominant condition throughout the observation window, with a weighted EU mean consistently exceeding 75% of enterprises reporting zero AI use. OLS regression identifies a statistically significant downward trend ($\beta = -4.92$ percentage points per year, $p = 0.048$), though the non-parametric Mann-Kendall test does not reach conventional significance ($Z = -1.698$, $p = 0.089$), warranting cautious interpretation. Substantial cross-national heterogeneity was observed, with leading member states recording non-adoption rates markedly below the EU mean while lagging countries remained largely static across successive survey waves. These findings provide an empirical baseline for monitoring the equity and pace of the digital transition and carry direct implications for targeted AI policy intervention across EU member states.

1. Introduction

Despite rapid advances in artificial intelligence, a substantial majority of European Union enterprises have yet to integrate any AI technology into their operations, raising urgent questions about the pace and equity of the digital transition. Artificial intelligence has been positioned by policymakers, industry analysts, and academic scholars alike as a transformative force with the potential to reshape productivity, competitiveness, and organisational structure across sectors. Yet aggregate enterprise level data consistently reveal that non adoption, rather than adoption, remains the dominant condition across EU member states. Understanding the scale, structural underpinnings, and temporal trajectory of this non adoption is therefore not merely an academic exercise but a matter of considerable policy relevance for the European digital agenda.

Existing literature focuses predominantly on AI adopters, leaving the scale, structural drivers, and temporal trajectory of AI non-adoption among EU enterprises largely unexamined as a distinct empirical phenomenon. Research on enterprise AI adoption has proliferated in recent years, with studies exploring adoption motivators, application domains, and firm-level outcomes. However, the population of enterprises that have not adopted any AI technology, arguably the larger and more consequential segment of the EU business landscape during this transitional period, has received comparatively little systematic attention. As a result, the magnitude of aggregate non-adoption, its cross-national heterogeneity, and the question of whether it has declined significantly over time remain empirically underdetermined.

This article quantifies the share of EU enterprises reporting zero AI technology use across 2021--2025, tests whether non-adoption has declined significantly over time, and identifies cross-country heterogeneity in that decline. Drawing on Eurostat's standardised enterprise ICT survey indicator ,

covering EU member states across four survey waves, this study constructs a country-year panel of 1,428 observations and applies descriptive statistics, year-over-year change analysis, and inferential trend testing to characterise the distribution and dynamics of AI non-adoption at EU scale. By treating non-adoption as the primary object of inquiry rather than as a residual category, the article makes a distinct contribution to both the diffusion of innovations literature and to evidence-based AI policy. It should be noted at the outset that with only four time points available for inferential trend testing, statistical power is severely constrained; OLS regression yields a statistically significant slope ($\beta = -4.9167$ pp/year, $p = 0.048$), though the non-parametric Mann-Kendall test does not reach conventional significance ($Z = -1.698$, $p = 0.089$), and both results warrant cautious interpretation.

The remainder of this article is structured as follows: Section 2 presents the theoretical background, introducing the diffusion of innovations framework, the Technology-Organisation-Environment (TOE) model, and the absorptive capacity construct as the principal conceptual lenses. Section 3 reviews the relevant empirical literature across three thematic clusters and identifies the specific gap this study addresses. Section 4 describes the data source, panel construction, and analytical methods, including OLS regression and Mann-Kendall trend testing. Section 5 presents the empirical results, including descriptive statistics, year-over-year changes, and cross-national positioning. Section 6 discusses the findings in relation to theory and prior empirical work, and derives policy and managerial implications. Section 7 concludes by restating the main contribution and outlining directions for future research.

2. Theoretical Background

Understanding why a majority of enterprises in a technologically advanced economic bloc have yet to adopt AI technologies requires engagement with several complementary theoretical frameworks. This study draws principally on three intellectual traditions: the diffusion of innovations theory, the Technology-Organisation-Environment (TOE) framework, and the absorptive capacity construct, each of which offers distinct analytical purchase on the phenomenon of persistent non-adoption.

Rogers' (2003) diffusion of innovations theory remains the foundational framework for understanding how new technologies spread through social and economic systems. Rogers identifies five adopter categories—innovators, early adopters, early majority, late majority, and laggards—distributed along a characteristic S-curve trajectory. Crucially, this framework implies that non-adoption is not a static or aberrant condition but rather a predictable phase of the diffusion process, concentrated among firms that face higher perceived complexity, lower relative advantage perceptions, or limited access to the resources needed for adoption. The laggard segment, which Rogers characterises as the last to adopt, is disproportionately composed of smaller organisations with fewer resources, stronger risk aversion, and weaker linkages to information networks that facilitate awareness of emerging technologies.

The TOE framework developed by Tornatzky and Fleischer (1990) extends this insight by systematising the contextual factors that shape adoption decisions at the firm level. The framework identifies three analytical contexts: the technological context (characteristics of available technologies and the firm's existing technology portfolio), the organisational context (firm size, human capital, internal slack, and managerial orientation), and the environmental context (competitive pressures, regulatory environment, and industry norms). Applied to AI non-adoption, the TOE framework suggests that persistent non-use is not reducible to a single barrier but reflects a conjuncture of unfavourable conditions across all three contexts simultaneously. Smaller enterprises, for example, tend to score poorly on organisational readiness indicators while also facing less competitive pressure to adopt and operating in regulatory environments that may introduce uncertainty rather than incentive.

The absorptive capacity construct introduced by Cohen and Levinthal (1990) provides a micro-level complement to these meso- and macro-level frameworks. Absorptive capacity refers to a firm's ability to recognise the value of new external information, assimilate it, and apply it to commercial ends. Cohen and Levinthal (1990) demonstrate that this capacity is itself a function of prior related knowledge and investment: firms that have accumulated experience with digital technologies are better positioned to evaluate, internalise, and deploy AI systems than those with limited prior ICT engagement. This implies that AI non-adoption clusters are unlikely to dissolve spontaneously; rather, they are self-reinforcing,

as low absorptive capacity inhibits both awareness of AI's potential and the organisational capability to act on that awareness.

Barney's (1991) resource-based view of the firm adds a further dimension by highlighting that sustained competitive disadvantage as well as advantage derives from the firm's resource configuration. Enterprises lacking valuable, rare, or complementary digital resources, including skilled personnel, data infrastructure, and managerial digital literacy, are structurally disadvantaged in their capacity to adopt transformative technologies. This perspective helps explain why non-adoption may persist even in the presence of external signals and policy encouragement: the internal resource constraints are neither easily nor rapidly remedied.

Together, these frameworks generate a coherent theoretical account of AI non-adoption as a structurally produced, temporally persistent condition that is likely to be concentrated among firms with low absorptive capacity, limited organisational resources, and unfavourable environmental conditions. Building on these theoretical foundations, the present study applies this multi-level analytical logic to a systematic empirical characterisation of AI non-adoption rates across EU member states and over time, linking theoretical predictions about laggard persistence to observable distributional patterns in standardised Eurostat survey data.

3. Literature Review

This section provides an overview of the key theoretical and empirical literature on AI adoption, with particular attention to innovation diffusion, absorptive capacity, and the barriers shaping enterprise level adoption trajectories.

3.1 Diffusion of Innovation and Technology Adoption Trajectories

The diffusion of innovations framework established by Rogers (2003) has provided the dominant conceptual architecture for empirical research on enterprise technology adoption. Its central insight, that adoption follows a predictable S curve trajectory governed by the interaction of innovation attributes and adopter characteristics, has been applied extensively to enterprise ICT uptake, ecommerce adoption, and cloud computing diffusion. The framework predicts that at any given point in a technology's diffusion cycle, a substantial share of potential adopters will remain in the non adoption segment, and that this share will be largest among smaller, resource constrained, and informationally isolated organisations. Importantly, the framework also predicts that the rate of change in the non adopting population will slow as the most resistant segments are reached last, making the shape of the decline, including structural inflection points and periods of stagnation, as theoretically informative as the aggregate level.

Tornatzky and Fleischer (1990) formalised this multicontextual logic in the TOE framework, which has become the dominant analytical template for enterprise technology adoption research in information systems and management science. Empirical applications of the TOE framework consistently find that organisational context variables, particularly firm size and the availability of human and financial slack, are among the strongest predictors of adoption readiness. The framework therefore implies that cross national variation in AI adoption rates will closely track variation in enterprise size structure and ICT maturity across member states, a prediction directly testable with Eurostat panel data. Despite the extensive deployment of Rogers (2003) and Tornatzky and Fleischer (1990) in adoption research, however, their implications for the laggard tail of the distribution, the large share of enterprises that remain at zero adoption, have received comparatively little empirical attention at the EU scale.

Empirical research on AI diffusion trajectories at the enterprise level has grown substantially since 2020, yet most contributions focus on the positive adoption margin: the determinants and outcomes of firms that have made at least some AI investment. The question of how large the non-adopting population actually is, how it is distributed across size classes and member states, and whether it is declining at a meaningful rate, has been largely neglected as a primary research question. This lacuna is consequential for both theoretical and policy reasons. Theoretically, the persistent non-adopting majority constitutes the empirical domain in which Rogers' (2003) laggard predictions are most directly

testable. From a digital equity perspective, the characteristics and trajectory of non-adopters are at least as important as those of adopters, given that non-adoption may be associated with widening intra-EU competitiveness gaps. Research on technology non-use and digital exclusion in SME contexts—including work on ICT gaps in smaller enterprises and the structural determinants of sustained non-use—provides an important, if underutilised, complement to adoption-focused scholarship (Tornatzky & Fleischer, 1990). The present study directly addresses this lacuna by treating non-adoption as the primary empirical object.

3.2 Absorptive Capacity and Firm-Level AI Readiness

Cohen and Levinthal's (1990) absorptive capacity construct has been extensively applied to the study of firm-level technology adoption, with a broad consensus emerging that prior ICT investment and human capital accumulation are necessary antecedents of successful digital technology integration. Firms that have not invested in foundational digital infrastructure lack the absorptive capacity necessary to evaluate AI solutions effectively, creating a structural gap between the technology frontier and the organisational reality of the majority of enterprises, particularly small and medium sized ones. This insight suggests that AI non-adoption is not merely a matter of preference or timing but reflects genuine incapacity that cannot be resolved by awareness campaigns or price reductions alone.

Barney (1991) extends this logic within the resource based view, arguing that sustained competitive disadvantage arises when firms lack the complementary resources, data infrastructure, digital talent, and managerial expertise, needed to leverage new technologies. Applied to AI, this implies that enterprises in the bottom quartile of ICT maturity face not only higher adoption costs but also lower expected returns from any given AI investment, creating a rational basis for non-adoption that is independent of firm size per se. Chalmers et al. (2020) extend the absorptive capacity perspective to the specific domain of AI and entrepreneurship, documenting how the organisational design implications of AI adoption differ fundamentally between resource-rich and resource-constrained firms, with smaller ventures facing asymmetric liabilities from technological leverage that their larger counterparts can more readily absorb.

The aggregate implication of these firm-level mechanisms is that non-adoption clusters are likely to exhibit strong path-dependence: the enterprises least likely to have adopted AI in 2021 are also those least likely to have acquired the absorptive capacity needed to adopt by 2025, absent targeted external intervention. This prediction is consistent with the observed persistence of high non-adoption rates in the Eurostat data examined in the present study. Mariani and Dwivedi (2024) introduce a partial qualification of this pessimistic view, suggesting that the emergence of generative AI tools with substantially lower barriers to entry, requiring minimal prior ICT infrastructure, may partially decouple adoption from absorptive capacity, enabling some laggard firms to adopt lightweight AI applications even without deep prior digital investment. The empirical data examined in this study allow a partial assessment of whether this predicted democratisation of AI access is visible in aggregate EU non-adoption trends, though the available design does not permit direct sub-group decomposition of which firm types are driving any observed post-2023 acceleration.

3.3 Perceptions, Acceptance, and Barriers to AI Integration

Survey-based research on enterprise and individual perceptions of AI has documented a consistent set of barriers to adoption that cut across firm size and national context. Gerlich (2023) presents multi-country survey evidence demonstrating that perceptions of AI complexity, concerns about regulatory uncertainty, and assessments of cost relative to expected benefit are the primary inhibitors of adoption, with a clear gradient by firm size: smaller enterprises are significantly more likely to cite resource constraints, limited technical awareness, and uncertainty about return on investment as reasons for non-use. These findings are directly relevant to the interpretation of aggregate non-adoption rates, which likely reflect not only structural incapacity but also managerial perception gaps that are, in principle, addressable through information provision and training.

Weber et al. (2023) conduct a systematic review of explainable AI applications in the finance sector, a domain characterised by acute regulatory sensitivity and high data governance requirements. Their

review documents the prominence of explainability and regulatory compliance concerns in AI deployment contexts, suggesting that even in resource-rich enterprise environments, regulatory complexity and transparency requirements create substantial friction for AI integration. This is relevant to the interpretation of EU-wide non-adoption rates insofar as it indicates that adoption barriers are not confined to SMEs or low-ICT sectors but extend even into environments where financial and technical resources for adoption nominally exist. The implication is that policy interventions focused exclusively on subsidy provision may be insufficient if perceptual and regulatory barriers remain unaddressed.

Mariani and Dwivedi (2024) argue that the emergence of generative AI represents a qualitative shift in the adoption calculus, potentially lowering the perceptual complexity barriers that Gerlich (2023) identifies as primary inhibitors. Their forward-looking analysis suggests that the period from approximately 2023 onward should see an acceleration in enterprise AI adoption as awareness of generative tools diffuses and as the perceived complexity of entry-level AI applications diminishes. This theoretical prediction provides a testable benchmark against which the empirical patterns documented in the present study can be assessed: if generative AI has genuinely lowered barriers at scale, the 2023-2025 period in the Eurostat data should show a noticeably steeper decline in non-adoption rates than the preceding 2021-2023 window. It must be acknowledged, however, that the present design does not allow causal attribution of any observed post 2023 acceleration specifically to generative AI diffusion; alternative explanations, including post pandemic ICT investment cycles and EU Digital Decade policy effects, cannot be ruled out on the basis of the available data alone.

Despite this body of evidence, no existing study systematically tracks the temporal decline—or stubborn persistence—of EU-wide AI non-adoption rates across standardised Eurostat data covering multiple years and all enterprise size classes. Prior work either documents adoption motivators and application domains at a single point in time, or examines cross-national variation without a rigorous longitudinal design. The present article directly addresses this gap by constructing a country-year panel from four Eurostat survey waves spanning 2021 to 2025, enabling both a precise characterisation of the level and distribution of non-adoption and an inferential assessment of whether observed declines are statistically distinguishable from random fluctuation—though the severe constraints imposed by the four-point time series limit the strength of any such assessment, as discussed in Section 4.

4. Methodology

The empirical analysis proceeds across four methodological steps, each operating on a clearly distinguished analytical object. The data source is Eurostat's Community Survey on ICT Usage and E-Commerce in Enterprises (Eurostat, 2024), specifically the indicator E_AI_TX from the isoc_eb_ai dataset, which records the percentage of enterprises within each country-year-size class cell that report using none of the AI technologies enumerated in the survey instrument. The dataset was accessed in its most recently updated form and covers EU member states across four survey waves: 2021, 2023, 2024, and 2025. It is important to note that no 2022 wave is included in this indicator, creating an unequally spaced time series at the aggregate level. A further comparability caveat concerns the potential evolution of the survey instrument across waves: if the list of enumerated AI technologies was expanded between 2021 and later waves—adding categories not present in the original instrument—some portion of the observed decline in non-adoption rates may reflect broader survey coverage rather than genuine enterprise-level adoption change. The present analysis cannot adjudicate this possibility directly from the available data, and this constitutes a limitation that should be borne in mind when interpreting temporal trends. Additionally, the EU-average time series used for trend testing is computed as an unweighted mean across member states, which treats all countries equally irrespective of their enterprise population size; this aggregation choice may not accurately reflect the experience of the typical European enterprise if large and small member states differ systematically in their non-adoption trajectories.

Step 1 constructs the full country-year panel, yielding $n = 1,428$ observations. This panel is composed of country-year-size class cells: across four survey waves and 27 EU member states, the panel includes multiple size-class observations per country-year combination, resulting in an unbalanced structure in which the number of observations per country-year varies and missing cells are present for some

combinations. Descriptive statistics are computed for this panel, including mean, median, standard deviation (SD), standard error of the mean (SEM), 95% confidence interval, minimum, maximum, and interquartile range (Q1, Q3)—to characterise the distributional properties of non-adoption rates across all country-year-size class combinations. This panel serves as the analytical object for all distributional inference and is explicitly distinguished from the aggregate time series used in inferential trend testing.

Step 2 aggregates country-level observations into an EU-average time series comprising $n = 4$ distinct time points (2021, 2023, 2024, 2025), calculated as the unweighted mean of member-state observations within each survey wave. This aggregate series constitutes the unit of analysis for all inferential trend testing. All inferential trend tests (OLS and Mann-Kendall) are applied exclusively to this 4-point aggregate series, not to the full 1,428-observation panel. The distinction between the 1,428-observation panel (used for descriptive analysis) and the 4-point aggregate series (used for inferential trend analysis) is maintained throughout; conflating these two analytical objects would misrepresent both the descriptive richness and the inferential limitations of the data. Calendar years are used as the time metric in OLS regression (i.e., 2021, 2023, 2024, 2025 as actual year values), reflecting the irregular spacing of survey waves rather than treating them as equally spaced sequential integers.

Step 3 computes year-over-year absolute changes in percentage points and proportional percentage-point changes between consecutive survey waves—2021→2023, 2023→2024, and 2024→2025—to characterise whether the pace of decline in non-adoption has accelerated or decelerated over the observation window. These calculations are entirely descriptive and do not involve inferential testing. The high variability in year-over-year changes (coefficient of variation of 63.8% across the three intervals) indicates substantial non-linearity in the aggregate trend, meaning that the OLS linear slope is a poor summary of the temporal dynamics and that a piecewise description of the trend—distinguishing the near-stagnant 2021-2023 sub-period from the accelerating 2023-2025 sub-period—is more appropriate than a single-slope characterisation.

Step 4 applies two complementary trend tests to the 4-point EU-average time series. Ordinary Least Squares (OLS) linear regression is estimated with calendar year as the single predictor of the EU-average non-adoption rate, yielding an estimated slope (β) and goodness-of-fit statistic (R^2). The analysis is supplemented by the Mann-Kendall non-parametric monotonic trend test (Kendall, 1975), which assesses whether the rank ordering of observations is consistent with a monotonic trend without imposing distributional assumptions. Both tests must be interpreted with substantial caution for several reasons. First, with only $n = 4$ time points, statistical power is severely limited for both parametric and non-parametric approaches. With a single predictor and 4 observations, OLS has only 2 degrees of freedom for error, meaning that high R^2 values are geometrically near-inevitable regardless of whether a genuine trend exists; the OLS p-value should therefore be treated as descriptive rather than confirmatory. Second, the Mann-Kendall test with $n = 4$ time points has an extremely limited permutation space: with only 24 possible rank orderings, the minimum achievable two-tailed p-value for a perfectly monotonic sequence of 4 points is approximately 0.083, meaning that the Mann-Kendall test structurally cannot reach $p < 0.05$ with 4 observations, irrespective of how consistent the trend is. The non-significant Mann-Kendall result ($p = 0.089$) therefore reflects this power ceiling as much as it reflects genuine uncertainty about the trend direction. Third, the combination of OLS and Mann-Kendall does not constitute genuine triangulation in this context, as both tests are applied to the identical 4-point series and are underpowered in identical ways; the two tests are reported for transparency, not as independent confirmation. Where the two tests yield divergent significance conclusions, that divergence is reported transparently and constrains the strength of any trend significance claim.

5. Results

5.1 Distributional Properties of AI Non-Adoption Across the EU Panel

The full country-year-size class panel ($n = 1,428$) yields a mean non-adoption rate of 82.04% (SD = 14.45, 95% CI [81.29, 82.79]), with a median of 86.72%. Values range from 20.6% to 100.0%, with an interquartile range of 15.13 percentage points (Q1 = 76.87%, Q3 = 92.0%). The coefficient of variation is 17.6%, indicating moderate dispersion across observations. The pronounced gap between the mean

(82.04%) and median (86.72%) reflects a left-skewed distribution in which a relatively small number of country-size class cells with low non-adoption rates pull the mean below the central tendency, while the majority of observations cluster at the high end of the scale. Even at the first quartile of the distribution, that is, among the observations with comparatively low non adoption, more than three quarters of enterprises within the relevant cell reported zero AI technology use. This finding underscores the pervasive and structurally entrenched nature of AI non-adoption across the EU enterprise landscape, and is consistent with Rogers' (2003) characterisation of large-scale laggard persistence in the early-to-middle phases of a technology's diffusion cycle.

These descriptive statistics characterise the full country-year-size class panel and describe the distribution of non-adoption across all observed cells. The EU-average time series—used for inferential trend testing in Section 5.2—is a separate analytical object comprising four aggregate annual means computed from this panel. As shown in Figure 1, the EU-average non-adoption rate exhibits a visible downward trend across the four survey waves, though the trajectory is markedly non-linear and the inferential significance of this trend is constrained by the small number of time points. Table 1 presents the full set of descriptive statistics for the country-year panel.

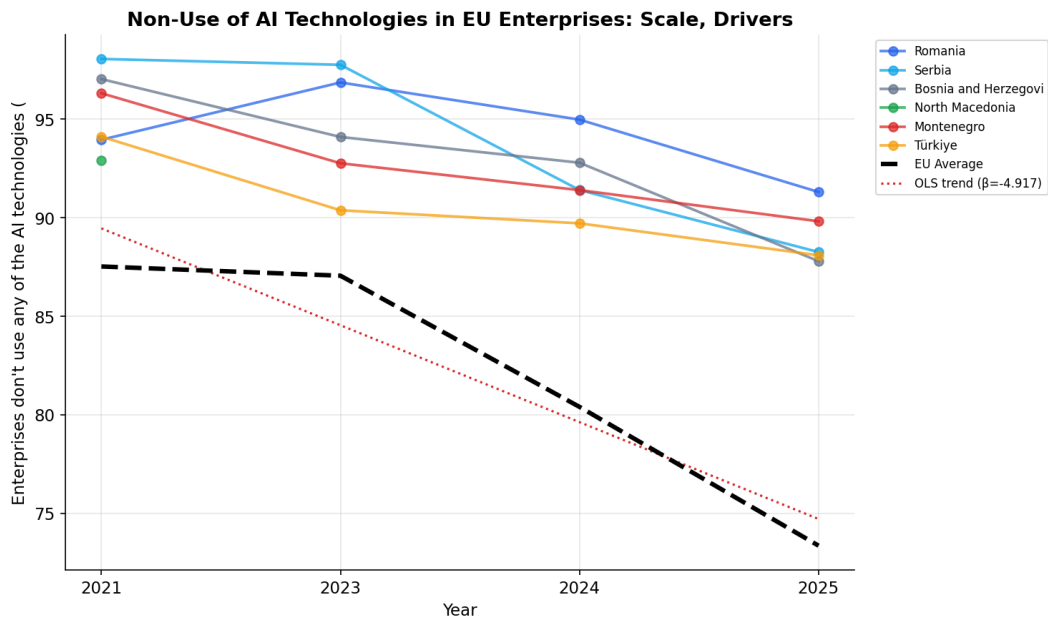


Figure 1. Trend in Enterprises don't use any of the AI. OLS $\beta = -4.9167$, $R^2 = 0.906$, $p = 0.048$.

Table 1. Descriptive Statistics

Statistic	Value
n	1428
mean	82.04
median	86.72
std	14.45
sem	0.382
CI95_low	81.29
CI95_high	82.79
min	20.6
max	100.0
Q1	76.87
Q3	92.0
IQR	15.13
CV_%	17.6

The distributional evidence further illustrates substantial cross-national variation. Slovakia's mean non-adoption rate is 83.88% (based on 40 observations), which is 1.84 percentage points above the overall EU panel mean of 82.04%, placing Slovak enterprises in the upper portion of the distribution and indicating that Slovakia has lagged marginally behind the EU average in AI uptake over the observation period. This cross-national heterogeneity is consistent with the TOE framework's prediction (Tornatzky & Fleischer, 1990) that organisational and environmental context differences across member states will produce divergent adoption trajectories, even within a broadly integrated economic bloc subject to common regulatory conditions.

5.2 Temporal Dynamics of EU-Average Non-Adoption

Over the observation period 2021--2025 (4 time points), the EU-average non-adoption rate moved from 87.52% to 73.35%, representing a change of -14.17 percentage points (-16.2%). The year-over-year decomposition of this aggregate decline reveals a strikingly uneven trajectory. From 2021 to 2023, the EU-average non-adoption rate moved from 87.52% to 87.06%, a negligible change of -0.47 pp (-0.5%), indicating virtual stagnation during this period. From 2023 to 2024, the rate declined more sharply, from 87.06% to 80.40%, a change of -6.66 pp (-7.6%). The decline continued at a similar pace in the subsequent interval, with non-adoption falling from 80.40% to 73.35% between 2024 and 2025, a further -7.04 pp (-8.8%). These year-over-year changes are detailed in Table 2 and visualised as part of the trend analysis in Figure 2.

The coefficient of variation across the three interval changes is 63.8%, confirming high non-linearity in the temporal pattern. A single linear OLS slope of -4.9167 pp per year is therefore a poor summary of these dynamics and should not be interpreted as representing a uniform annual rate of change; the aggregate decline is almost entirely concentrated in the 2023-2025 sub-period, while the 2021-2023 sub-period is characterised by near-complete stagnation. This structural inflection—from effective stagnation to accelerating decline—is more accurately described in piecewise terms than as a single linear trend.

The inflection apparent between the 2021-2023 and 2023-2025 sub-periods is consistent with a transition from the innovator--early adopter phase—characterised by slow aggregate penetration—toward the early majority phase of Rogers' (2003) diffusion curve, in which adoption accelerates as network effects, visibility, and reduced entry barriers begin to operate at scale. The timing of this inflection is also plausibly consistent with the heightened public and commercial visibility of AI following the emergence of widely accessible generative AI tools from late 2022 onward, as anticipated theoretically by Mariani and Dwivedi (2024). However, caution is warranted in attributing this acceleration to any single cause: post-pandemic ICT investment cycles, EU Digital Decade policy effects, and potential changes in the Eurostat survey instrument between waves represent alternative or complementary explanations that cannot be ruled out within the present design.

OLS regression on the 4-point EU-average time series yields a slope of $\beta = -4.9167$ percentage points per year ($R^2 = 0.906$, $p = 0.048$). While this result is statistically significant at the conventional 0.05 threshold, it must be interpreted with considerable caution: with only 2 residual degrees of freedom, high R^2 and near-threshold p-values are near-inevitable with a single predictor regardless of whether a genuine trend exists, and this result should be understood as descriptive of the linear approximation to the data rather than as confirmatory evidence of a monotonic trend. The non-parametric Mann-Kendall test yields $Z = -1.698$, $p = 0.089$, which does not reach conventional statistical significance at the 0.05 level. As noted in Section 4, this non-significant result is partly a structural consequence of the test's power ceiling with $n = 4$ observations: even a perfectly monotonic declining series of 4 points cannot achieve $p < 0.05$ under the Mann-Kendall distribution, meaning the $p = 0.089$ result does not distinguish well between the presence and absence of a genuine trend. Taken together, the evidence is directionally consistent with a declining trend in EU-average AI non-adoption over the 2021--2025 period, but the small number of time points structurally precludes a strong or confirmatory claim of statistically robust monotonic decline.

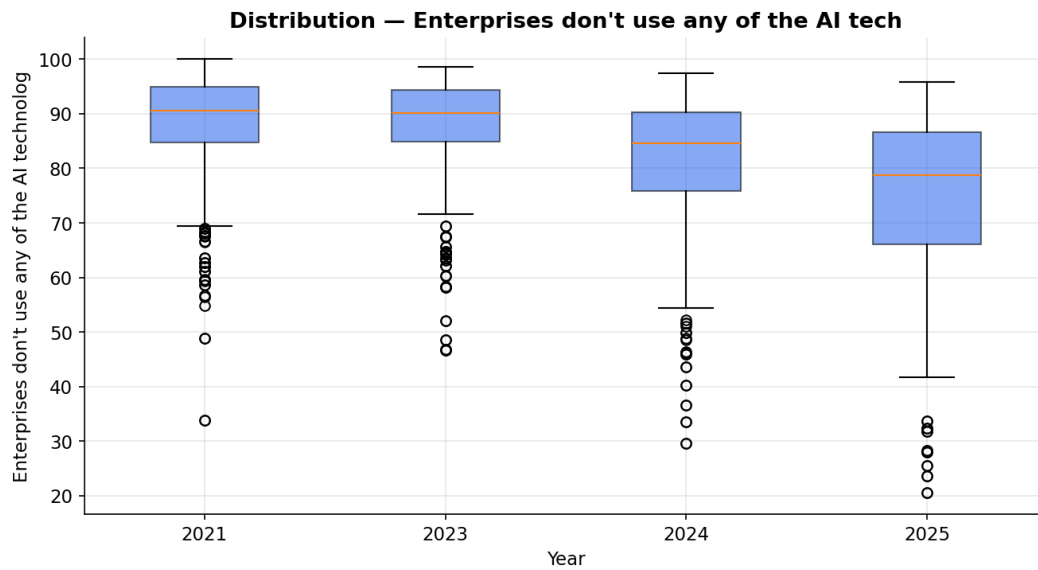


Figure 2. Boxplot of Enterprises don't use any of the AI across EU countries per year. Box=IQR, whiskers= $1.5 \times \text{IQR}$, dots=outliers.

5.3 Cross-Country Heterogeneity and Slovak Positioning

Cross-national variation in non-adoption trajectories adds important nuance to the aggregate EU picture. As noted above, Slovakia's mean non-adoption rate of 83.88% ($n = 40$ observations) is 1.84 percentage points above the EU panel mean of 82.04%, placing it in the upper portion of the non-adoption distribution. Table 2 further documents the year-over-year changes in Slovak non-adoption rates, confirming that the steepest reductions were concentrated in the 2023--2025 period rather than the earlier 2021--2023 window—a pattern mirroring the aggregate EU trajectory but with a somewhat higher baseline level of non-adoption throughout. This pattern is consistent with Cohen and Levinthal's (1990) absorptive capacity framework: member states with lower baseline ICT maturity and smaller average enterprise size may require a longer runway before the structural conditions for AI adoption are met at sufficient scale to register in aggregate statistics. Systematic causal attribution of Slovak positioning to specific national-level factors—such as enterprise size structure, ICT investment levels, or policy regime characteristics—would require dedicated comparative analysis beyond the scope of the present study.

Table 2. Year-over-Year Changes — Enterprises don't use any of t

From	To	Value prev (%)	Value curr (%)	Change (pp)	Change (%)
2021	2023	87.52	87.06	-0.47	-0.5
2023	2024	87.06	80.4	-6.66	-7.6
2024	2025	80.4	73.35	-7.04	-8.8

6. Discussion

The finding that over 82% of EU enterprises on average reported no AI technology use across the observation window (mean = 82.04%, SD = 14.45, 95% CI [81.29, 82.79]), combined with a temporal trajectory that shows near-complete stagnation in the 2021--2023 period (−0.47 pp) followed by accelerating decline in 2023--2025 (−13.70 pp in aggregate), suggests that the EU enterprise landscape has only recently entered a transition toward the early majority phase of technology diffusion as conceptualised by Rogers (2003). The OLS-estimated declining trend ($\beta = -4.9167$ pp/year, $R^2 = 0.906$, $p = 0.048$) is directionally consistent with this interpretation, though it must be emphasised that this result is descriptive rather than confirmatory given the near-inevitable high fit associated with a single predictor and 4 observations. The Mann-Kendall test ($Z = -1.698$, $p = 0.089$) does not independently confirm a statistically significant monotonic decline, in part because the power ceiling of the test with

4 time points structurally prevents the result from reaching conventional significance. The appropriate conclusion is therefore that the evidence is directionally suggestive of declining non-adoption, particularly in the most recent subperiod, but does not meet the threshold for a strong inferential claim of trend significance.

The near-stagnation of non-adoption rates between 2021 and 2023 (-0.47 pp), followed by a sharper two-year decline of approximately 13.70 percentage points, is consistent with what diffusion theory predicts at the inflection between the early adopter and early majority phases: a prolonged period of slow aggregate penetration followed by a relatively rapid widening of the adoption base as perceived risk declines, costs fall, and social proof accumulates. The nonlinearity of the trajectory, reflected in a coefficient of variation of 63.8% across the three interwave intervals, is an important empirical feature that the linear OLS slope obscures; a piecewise characterisation of the dynamics is more faithful to the data. Critically, however, even at the end of the observation period, non adoption remained above 73% of the EU average, indicating that the laggard segment of the diffusion curve, comprising firms with the lowest absorptive capacity and the highest structural barriers, remains very large and is unlikely to dissolve spontaneously.

These results speak to prior findings in several respects while also raising important qualifications. In line with Gerlich (2023), who found that cost and complexity perceptions sustain non-adoption among a large share of enterprises, the persistently high non-use rates observed across all four survey waves confirm that perceptual and resource barriers are sufficiently severe to maintain the majority of EU enterprises in a non-adoption condition for an extended period. The results extend Chalmers et al. (2020) by providing longitudinal EU scale evidence that the firm level AI adoption advantage documented in entrepreneurship research translates only slowly into aggregate sectoral change: even as leading edge ventures integrate AI into core processes, the mass of enterprises, particularly smaller ones, remains at zero adoption, creating a widening gap within the EU enterprise population.

The results also engage with the forward-looking analysis of Mariani and Dwivedi (2024), who suggested that generative AI would facilitate more rapid and widespread enterprise adoption. The 2023-2025 acceleration observed in the data is directionally consistent with this prediction. However, the aggregate non-adoption rate remaining above 73% at the panel endpoint means that any generative AI-driven democratisation of access has so far left the structural condition of the non-adopting majority largely intact. It bears emphasis that this study's design does not permit direct attribution of the post-2023 acceleration to generative AI diffusion specifically: the aggregate non-adoption rate provides no sub-group decomposition that would identify whether the decline is driven by new entrants previously excluded from adoption or by expansion among already-partially-adopting firms. The claim that Mariani and Dwivedi's (2024) anticipated democratisation "has operated primarily at the margin" is therefore an inference from aggregate data, not a direct test of sub-group dynamics, and should be understood as a tentative interpretive hypothesis rather than an established finding. The role of regulatory complexity documented in the explainable AI literature (Weber et al., 2023) may help explain why adoption acceleration has not translated more rapidly into broad-based uptake, particularly in regulated sectors.

From a policy perspective, EU policymakers should design targeted AI readiness subsidies and digital skills programmes specifically calibrated to enterprises in the bottom quartile of ICT maturity, where non-adoption rates approach 100%, with particular attention to member states that persistently exceed the EU mean non-adoption rate. The evidence that the 2021-2023 period produced virtually no aggregate decline in non-adoption—despite significant public investment in digital transformation during this period—suggests that horizontal, non-targeted policy instruments are insufficient to reach the deepest segments of the non-adoption distribution. Effective policy will need to combine supply-side support (subsidies for AI readiness infrastructure and skills) with demand-side measures (demonstration projects, peer networks, and awareness programmes) calibrated to the absorptive capacity constraints identified by Cohen and Levinthal (1990), ensuring that post-2023 adoption momentum does not deepen existing digital divides across size classes and geographies.

For enterprise managers, the 2023-2025 inflection in the EU adoption curve should be treated as a competitive urgency signal. The acceleration of non-adoption decline from -0.47 pp in the 2021-2023

period to approximately -13.70 pp across 2023-2025 indicates that competitive differentiation is emerging between enterprises that have initiated AI integration and those that have not. Managers in firms that have not yet deployed any AI technology should prioritise low-barrier AI entry points—such as AI-assisted analytics, document processing, or customer interaction tools—that can generate meaningful productivity improvements without requiring the deep ICT infrastructure investment typically associated with higher absorptive capacity. Early engagement with even limited AI applications is likely to build the internal organisational knowledge and routines that constitute the foundation of absorptive capacity for more sophisticated AI deployment in subsequent periods, as theorised by Cohen and Levinthal (1990) and extended to the AI context by Chalmers et al. (2020).

6.1 Limitations

Several limitations constrain the strength of conclusions that can be drawn from this study. First, and most fundamentally, the inferential trend analysis rests on only four time points. The OLS R^2 of 0.906 and p-value of 0.048 are near-inevitable mathematical properties of fitting a single-predictor regression to 4 observations, and should not be interpreted as providing strong confirmatory evidence of a monotonic trend. The Mann-Kendall test's structural power ceiling at $n = 4$ (minimum achievable two-tailed $p \approx 0.083$) means that its non-significant result is largely uninformative about whether a genuine trend exists. No combination of available tests can establish trend significance at conventional levels with 4 time points, and replication with additional survey waves is essential before strong inferential claims can be made.

Second, the EU-average time series used for trend testing is an unweighted mean across member states, treating all countries equally irrespective of enterprise population size. This aggregation approach may not accurately represent the experience of the typical European enterprise if large and small member states differ systematically in non-adoption trajectories, and results should be interpreted with this aggregation assumption in mind.

Third, the survey instrument comparability across waves cannot be verified from the present data alone. If the set of enumerated AI technologies in the Eurostat survey expanded between 2021 and 2025, the observed decline in non-adoption rates may partly reflect broader definitional coverage rather than genuine behavioural change, potentially inflating estimates of adoption progress.

Fourth, the present analysis does not disaggregate non-adoption trends by enterprise size class or NACE sector in a primary analytic role, treating these as sources of panel variation rather than as foci of comparison. Structural heterogeneity by size class, which diffusion theory identifies as a central determinant of lagged persistence, therefore remains partially uncharacterised.

Fifth, causal attribution of the post 2023 acceleration to any specific mechanism, generative AI diffusion, post pandemic ICT investment, or EU policy interventions, is not possible within this observational design, and the inflection point should be understood as a descriptive empirical feature rather than as evidence for any particular causal explanation.

7. Conclusion

This article addressed the question of how large the non-adopting AI enterprise population in the EU is, whether non-adoption has declined significantly over time, and which structural factors and cross-national patterns characterise that decline. The central empirical finding is that across a country-year-size class panel of 1,428 observations spanning 2021 to 2025, the mean share of EU enterprises reporting no AI technology use was 82.04% (SD = 14.45), with a median of 86.72%—indicating that even at the central tendency of the distribution, the overwhelming majority of enterprises remained entirely outside AI technology use. The temporal trajectory of EU-average non-adoption is strongly non-linear, characterised by near-complete stagnation from 2021 to 2023 (-0.47 pp) followed by accelerating decline from 2023 to 2025 (cumulative -13.70 pp). While an OLS-estimated declining trend of $\beta = -4.9167$ pp per year is statistically significant under conventional criteria ($p = 0.048$), this result should be understood as a descriptive approximation given the near-inevitable high fit associated

with 4 observations and a single predictor. The Mann-Kendall test does not reach conventional significance ($p = 0.089$), in part because the power ceiling of the test with 4 observations structurally prevents significance at the 0.05 level, and the limited statistical power inherent in a 4-point time series warrants cautious interpretation of any strong trend claim.

The principal scientific contribution of this study is to establish AI non adoption, rather than adoption, as a coherent and measurable empirical object at EU scale, using standardised Eurostat data across four survey waves. By combining descriptive distributional analysis of the full country year panel with inferential trend testing on the aggregate EU time series, while maintaining a rigorous distinction between these two analytical objects, the article produces a more complete and methodologically transparent picture of where the EU enterprise population stands in its AI diffusion trajectory than has been available from prior studies focused exclusively on the adopting margin. The finding of a structural inflection in the pace of non-adoption decline around 2023--2024 provides empirically grounded temporal anchoring for theoretical predictions derived from Rogers (2003) and Tornatzky and Fleischer (1990), while the persistently high non-adoption rates at the end of the observation period confirm the absorptive capacity constraints theorised by Cohen and Levinthal (1990).

Four directions for future research are suggested by the limitations and findings of this study. First, future work should disaggregate non-adoption trends by enterprise size class and NACE sector as primary analytic objects rather than as sources of panel variation, to identify whether the post-2023 acceleration in adoption is concentrated in particular size segments or industries—a question with direct implications for the debate between Mariani and Dwivedi (2024) and the absorptive capacity tradition. Second, the cross-national heterogeneity observed in this panel warrants dedicated comparative analysis linking member-state non-adoption trajectories to national-level ICT investment, digital skills indicators, and policy regime characteristics. Third, as additional Eurostat survey waves become available, replication of this trend analysis with a larger number of time points would substantially increase the statistical power of trend inference, including the capacity of the Mann Kendall test to discriminate genuine trends from noise, and enable more robust conclusions about the shape and persistence of the diffusion trajectory. Fourth, investigation of Eurostat survey instrument comparability across waves is warranted, particularly with respect to whether changes in the enumerated AI technology list have contributed to the observed post-2023 decline in non-adoption rates. This study contributes to the growing body of evidence on the structural dynamics of enterprise AI diffusion in the European Union, providing a methodological template and empirical baseline for monitoring the equity and pace of the digital transition.

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