

Readiness, Not Restriction: Firm Size, Digital Infrastructure, And the Conditional Effect of Regulatory Intensity on Enterprise AI Adoption in the European Union

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ABSTRACT

This paper examines why European Union member states with broadly similar regulatory environments show large differences in enterprise adoption of artificial intelligence (AI). Using a ten-country sample drawn from Eurostat's Community Survey on ICT Usage in Enterprises (2023–2025) and the OECD Digital Services Trade Restrictiveness Index (Digital STRI), we test whether firm size, digital infrastructure readiness, and regulatory intensity explain differences in AI adoption across countries and firm-size classes. An initial specification, built by pooling nine conceptually distinct Eurostat AI-use indicators, several measuring non-adoption rather than adoption, and two incompatible denominators into a single dependent variable, produced results that could not be interpreted as measuring AI adoption. After restricting the sample to a single, comparably defined indicator, the usable sample fell from 731 to 65 observations. Because the corrected sample contains only ten country clusters, we cross-check conventional cluster-robust inference against a t-distribution correction and a wild cluster bootstrap using the full population of sign-flip permutations. Under this stricter inference, small and medium enterprises show a robust adoption gap of 10 to 14 percentage points relative to large enterprises, while the interaction between regulatory intensity and firm size remains significant: the small-firm adoption gap narrows as regulatory intensity rises. Basic cloud computing readiness has a large positive point estimate but does not survive the wild cluster bootstrap. We report this discrepancy explicitly and document the data and specification corrections underlying the final analysis. These results further indicate that enterprise-level characteristics remain important even when national regulatory conditions are broadly comparable. The findings suggest that policies aimed at strengthening enterprise capacity and digital infrastructure, rather than adjusting the general level of digital regulation, are more likely to narrow this gap.

Keywords: enterprise AI adoption; firm size; regulatory intensity; digital infrastructure; Eurostat

INTRODUCTION

Background

Artificial intelligence (AI) has become an increasingly important component of enterprise digital transformation and economic competitiveness. Across the European Union (EU), the adoption of AI technologies by enterprises has increased rapidly in recent years. Eurostat reports that the share of EU enterprises using at least one AI technology increased from 8.1% in 2023 to 13.5% in 2024 and 20.0% in 2025 (Eurostat, 2025b). Despite this overall increase, substantial differences remain across member states. In 2025, enterprise AI adoption reached

42.0% in Denmark and 37.8% in Finland, compared with 5.2% in Romania, 8.4% in Poland, and 8.5% in Bulgaria (Eurostat, 2025b).

These differences are important because EU member states operate within a broadly shared institutional and regulatory environment. Common European frameworks, including the General Data Protection Regulation (GDPR) and the emerging EU Artificial Intelligence Act, establish common regulatory requirements across member states. Nevertheless, substantial differences in enterprise AI adoption persist. This suggests that national adoption outcomes may also depend on differences in firms' technological capabilities, organizational characteristics, and exposure to regulatory constraints.

Firm size is particularly relevant to this question. Large enterprises generally possess greater financial resources, technical expertise, and organizational capacity to invest in emerging technologies than small and medium-sized enterprises (SMEs). As a result, differences in firm size may contribute substantially to the uneven diffusion of AI across countries. At the same time, access to basic digital infrastructure, such as cloud computing, may determine whether firms possess the technological foundation necessary to implement AI systems.

Regulatory conditions represent another potentially important factor. Regulations governing digital services and cross-border data flows may increase compliance requirements and affect the cost of deploying data-intensive technologies. However, the relationship between regulation and AI adoption is not necessarily straightforward. Regulation can impose additional costs, but it may also provide institutional stability, trust, and predictable operating conditions. The empirical relationship therefore requires direct examination rather than an assumption that stronger regulation necessarily reduces technological adoption.

The problem

Existing research identifies several barriers to enterprise AI adoption, including implementation costs, shortages of skilled workers, technological limitations, organizational resistance, data-related concerns, and regulatory complexity. However, these factors do not necessarily affect all enterprises equally. In particular, smaller firms may face greater difficulties in financing technological investment and absorbing fixed compliance costs than larger firms.

Data governance provides one possible mechanism through which regulatory conditions may influence AI adoption. Data localization and restrictions on cross-border data flows can require firms to modify their data infrastructure or compliance practices, potentially increasing the cost of deploying data-intensive technologies. Previous research and case evidence, including India's payment-data localization policy, illustrate how such requirements can generate additional compliance costs for firms that lack existing local infrastructure.

Whether similar mechanisms affect enterprise AI adoption across EU member states, however, remains an empirical question. EU countries share a common regulatory baseline, but they differ in their levels of digital development, enterprise structure, and measured restrictions on digital services. Examining these differences provides an opportunity to test whether regulatory intensity is associated with AI adoption after accounting for firm size and digital infrastructure readiness.

This study therefore focuses on three potential determinants of enterprise AI adoption: **firm size, digital infrastructure readiness, and regulatory intensity**. In addition to examining their individual associations with AI adoption, the study investigates whether regulatory intensity changes the adoption gap between small, medium, and large enterprises.

Research question

This study addresses the following research question: To what extent do firm size, digital infrastructure readiness, and national regulatory intensity explain variation in enterprise AI adoption across selected EU member states between 2023 and 2025, and does regulatory intensity moderate the relationship between firm size and AI adoption?

Contribution of the Study

This study contributes to the literature in three ways.

First, it provides a cross-country empirical analysis of enterprise AI adoption using harmonized Eurostat data from selected EU member states. Rather than relying on individual country case studies, the analysis compares countries within a broadly shared institutional environment.

Second, the study explicitly considers **firm-size heterogeneity**. Rather than treating enterprise AI adoption as a uniform national outcome, it examines whether small, medium, and large enterprises respond differently to digital infrastructure and regulatory conditions.

Third, the study places particular emphasis on statistical inference in a small-cluster setting. After correcting the construction of the dependent variable, the usable sample contains 65 observations distributed across ten countries. Because observations are clustered at the country level, conventional cluster-robust standard errors may provide unreliable inference with so few clusters. The study therefore supplements conventional estimates with a t-distribution correction and a wild cluster bootstrap, providing a more conservative assessment of statistical significance.

The study consequently emphasizes not only the estimated relationships but also the uncertainty surrounding those estimates. This approach is particularly important when drawing conclusions from a relatively small cross-country panel.

LITERATURE REVIEW

Enterprise AI Adoption and Firm Size

Enterprise adoption of AI is influenced by a combination of technological, organizational, financial, and regulatory factors. Praveen et al. (2025) identify limited AI expertise, implementation costs, data privacy concerns, regulatory complexity, and organizational resistance as important barriers to enterprise AI adoption. Their analysis emphasizes the importance of training, scalable infrastructure, ethical governance, and organizational capacity in moving from experimental AI projects toward sustained deployment.

Lopez-Garcia and Manrique Rojas (2024) similarly identify implementation costs, shortages of skilled personnel, government regulation, and technological skepticism as important barriers across manufacturing and financial services. Their cross-country and cross-industry analysis indicates that the importance of individual barriers varies according to sector and national context, suggesting that AI adoption cannot be explained by a single universal factor.

Eskandarzadeh (2026) further emphasizes the interaction between technological, organizational, ethical, and societal factors. The study identifies data quality, talent shortages, algorithmic concerns, and organizational resistance as important constraints and argues that successful AI adoption requires both technological capability and appropriate human and organizational capacity.

A particularly important dimension of enterprise heterogeneity is **firm size**. Large enterprises generally have greater financial and organizational resources available for technology investment, while smaller enterprises may face greater constraints in financing implementation, acquiring specialized skills, and reorganizing existing business processes. These differences suggest that AI adoption may systematically vary across small, medium, and large enterprises even when firms operate within the same national regulatory environment.

The literature therefore provides a basis for treating firm size as an important explanatory variable rather than simply a control variable. However, existing studies often examine adoption barriers at the enterprise or industry level without directly testing whether regulatory conditions affect firms of different sizes differently. This provides a basis for examining the interaction between firm size and regulatory intensity in the present study.

Digital Infrastructure and AI Adoption

Beyond organizational characteristics, the availability of digital infrastructure represents an important prerequisite for enterprise AI adoption. AI systems frequently depend on computing resources, data storage, connectivity, and digital platforms capable of supporting data-intensive applications. Consequently, differences in the underlying digital infrastructure available to enterprises may contribute to differences in national AI adoption.

Cloud computing is particularly relevant because cloud services provide enterprises with scalable computing and storage capacity without requiring firms to develop all infrastructure internally. This can reduce the fixed technological requirements associated with adopting advanced digital technologies and may be especially relevant for smaller firms with limited capital resources.

The broader AI adoption literature supports the importance of technological readiness. Praveen et al. (2025) emphasize scalable infrastructure as a condition for sustainable AI deployment, while Eskandarzadeh (2026) identifies technological capability and data-related constraints as important dimensions of AI adoption. These findings suggest that enterprise AI adoption should not be interpreted solely through the lens of regulation or policy. Differences in technological readiness may also explain substantial variation in adoption outcomes.

The present study therefore incorporates basic digital infrastructure readiness into the empirical analysis. This allows the relationship between regulatory intensity and AI adoption to be examined while accounting for differences in the technological environment in which enterprises operate. In the empirical analysis, digital infrastructure readiness is operationalized specifically as the share of enterprises using basic paid cloud computing services, rather than a broader index of technological capability.

Regulation, Data Governance, and AI Adoption

Regulation represents another potential determinant of AI adoption. Government regulation may affect enterprise deployment through compliance costs, restrictions on data use, administrative requirements, and uncertainty regarding permissible technological applications. At the same time, regulation may provide benefits by establishing predictable standards, protecting data, and increasing trust in digital technologies. The direction and magnitude of the relationship between regulation and AI adoption therefore remain an empirical question.

Data localization provides one example of how digital regulation may affect technology deployment. Taylor (2020) describes data localization as a policy approach requiring data to be stored or processed within national borders and identifies a tension between data sovereignty and the economic benefits of cross-border data flows. Agata and Kibet (2025) similarly argue that localization requirements can restrict international data connectivity, although governments may adopt such measures in response to privacy, security, and regulatory concerns.

Klühl and Nordås (2025) provide further evidence that restrictions on cross-border data flows can affect the adoption of AI-enabled technologies. Their analysis suggests that restrictions on international data movement may slow technology adoption, with particularly important consequences for smaller economies. Selby (2017) additionally argues that localization policies can reflect broader strategic and economic considerations rather than privacy protection alone.

The India payment-data localization case illustrates a potential mechanism through which regulation can generate asymmetric costs. Foreign firms that lacked local infrastructure were required to make additional investments to comply with localization requirements, whereas firms that already maintained locally compliant systems faced lower adjustment costs. This mechanism suggests that regulatory requirements may have different effects depending on firms' existing resources and infrastructure.

However, the India case should not be interpreted as direct evidence that higher regulatory intensity causes lower AI adoption across EU countries. It represents a specific regulatory intervention in a particular sector and institutional environment. Its relevance to the present study is therefore conceptual: it illustrates one mechanism

through which regulatory restrictions could affect technology deployment and potentially interact with firm resources.

The present study tests this broader relationship using the OECD Digital Services Trade Restrictiveness Index as a measure of national regulatory intensity. This provides a quantitative measure that can be compared across the selected EU countries rather than relying on individual regulatory case studies.

Government Intervention and Digital Development

The relationship between government intervention and technological adoption is not necessarily negative. Research on national AI strategies demonstrates that governments can also promote technological development through investment in infrastructure, research, talent, and innovation ecosystems.

Dafri (2023), for example, examines the United Arab Emirates' approach to AI development and identifies government investment, infrastructure development, talent cultivation, institutional monitoring, and strategic partnerships as important components of its AI strategy. Goode, Kim, and Deng (2023) similarly examine Singapore's national AI strategy and emphasize government-supported research and development, talent development, innovation programs, and collaboration between public and private institutions.

These studies demonstrate that government involvement can support technological development when intervention is directed toward capability building and innovation. At the same time, the evidence does not imply that government intervention is universally beneficial. Rather, its effects depend on the type of policy, institutional context, implementation, and existing technological capabilities.

For the present study, this literature provides an important qualification to a simple negative interpretation of regulatory intensity. A positive or insignificant coefficient on regulatory intensity would not necessarily contradict the broader literature on regulatory barriers, because regulation can simultaneously impose compliance requirements and provide institutional benefits. The empirical objective is therefore to determine the net association observed within the selected EU sample.

Research Gap and Hypotheses

The literature reviewed above identifies three broad determinants relevant to enterprise AI adoption. First, enterprise characteristics, particularly firm size, influence the financial, organizational, and human resources available for AI implementation. Second, digital infrastructure provides an important technological foundation for AI deployment. Third, regulatory conditions may influence adoption through compliance costs, restrictions on data flows, and the institutional environment in which firms operate.

However, relatively limited empirical work combines these dimensions within a common cross-country framework while explicitly examining whether regulatory conditions affect different firm-size groups differently. Existing studies frequently focus on individual adoption barriers, industry-specific evidence, or national case studies. Evidence concerning the interaction between regulatory intensity and enterprise size remains comparatively limited.

This study addresses this gap by combining harmonized Eurostat enterprise AI-adoption data with the OECD Digital Services Trade Restrictiveness Index and digital infrastructure indicators across ten EU member states. The analysis focuses on whether firm size, digital readiness, and regulatory intensity are associated with differences in enterprise AI adoption and whether regulatory intensity moderates the adoption gap between firm-size classes.

Based on the literature, the study evaluates the following hypotheses:

H1: Large enterprises have higher AI adoption rates than small and medium-sized enterprises.

H2: Greater digital infrastructure readiness is positively associated with enterprise AI adoption.

H3: Higher regulatory intensity is associated with lower enterprise AI adoption.

H4: Regulatory intensity moderates the relationship between firm size and AI adoption, such that the adoption gap between smaller and larger enterprises differs across regulatory environments.

These hypotheses are evaluated empirically rather than treated as predetermined conclusions. In particular, the analysis considers whether the estimated relationships remain statistically supported under alternative inference procedures appropriate for the small number of country clusters.

METHODOLOGY

3.1 Data sources

The dependent variable is drawn from Eurostat's Community Survey on ICT Usage in Enterprises, dataset *isoc_eb_ai*, which reports the share of enterprises using AI technologies, broken down by country, enterprise size class, and survey year. The regulatory-intensity variable is the OECD Digital Services Trade Restrictiveness Index (Digital STRI), a country-level measure constructed from the OECD's regulatory database and policy indices. One control variable is drawn from the same Eurostat survey: cloud computing adoption, measured as the percentage of enterprises using basic paid cloud computing services. Table 1 summarizes the variables, their measurement, and their sources.

Variable	Role in Model	Definition / Measurement	Level of Variation	Source
AI Adoption	Dependent Variable	Percentage of enterprises using at least one AI technology for a listed business purpose	Country × Size × Year	Eurostat, <i>isoc_eb_ai</i>
Digital STRI	Main Explanatory Variable	OECD Digital Services Trade Restrictiveness Index	Country	OECD
Cloud Readiness	Control Variable	Percentage of enterprises using basic paid cloud computing services	Country × Size × Year	Eurostat, <i>isoc_eb_ai</i>
Firm Size	Structural Variable	Enterprise size class: 10–49, 50–249, or 250+ employees	Size Class	Eurostat, <i>isoc_eb_ai</i>
Year	Time Dimension	Survey year: 2021, 2023, 2024, or 2025, subject to indicator availability	Year	Eurostat
Country	Cross-Sectional Dimension	AT, BE, HR, DK, FI, FR, DE, NL, RO, SE	Country	Eurostat

Table 1 Variables, definitions, measurement, and data sources.

Note: Country codes follow Eurostat conventions.

Sample construction

The raw extract covers ten EU member states—Austria, Belgium, Croatia, Denmark, Finland, France, Germany, the Netherlands, Romania, and Sweden—three enterprise size classes, and survey years 2021, 2023, 2024, and 2025. The underlying Eurostat survey did not field the relevant indicator in 2022. Enterprise size classes follow the Eurostat convention: 10–49, 50–249, and 250 or more employees, with the largest class used as the reference category throughout. These ten countries were retained because they were the only EU member states with sufficiently complete coverage of the relevant AI-adoption indicator and the Digital STRI measure over the sample period; the selection therefore reflects data availability rather than a designed or random sample.

The final analytical sample is unbalanced because the selected AI-adoption indicator was not consistently available across all survey years and countries. The sample construction and resulting reduction in observations are described in Section 3.3.

A data quality correction: from $N = 731$ to $N = 65$

This subsection documents a data construction error identified after the initial regression results had already been produced and reported, and explains why correcting it substantially reduced the usable sample. We report this in detail, rather than only in summary, because the correction materially changes both the size and the interpretation of every coefficient in the model, and because the same error is easy to reproduce with Eurostat multi-indicator extracts if it is not checked for explicitly. Reporting the withdrawn specification alongside the corrected one, rather than silently replacing it, follows the logic of multiverse and specification-curve reporting (Steen, Tuerlinckx, Vanpaemel, & Gelman, 2016): when a defensible processing choice materially changes the result, showing both is more informative, and more honest about researcher discretion, than showing only the version that was ultimately kept.

The initial extract combined survey responses across nine conceptually distinct Eurostat indicator definitions (variable `indic_is`) into a single outcome column. These nine definitions include, alongside genuine AI-use measures, two indicators that record enterprises that do not use AI technologies because of data protection concerns or legal uncertainty; that is, non-adoption indicators recorded in the same column as adoption indicators. They also include an indicator for enterprises whose AI was developed in-house, which measures the sourcing of AI rather than its use, and indicators conditioned on a separate digital-intensity classification. Pooling these nine series and treating the result as one continuous adoption rate produced 731 usable observations after dropping rows missing a control variable. A second, compounding problem was identified in the unit field of the same extract: even within the single most defensible indicator (enterprises using AI for at least one listed business purpose), values were recorded under two different denominators, percentage of all enterprises and percentage of enterprises that already use at least one AI technology. These are not the same quantity, and averaging across them is not meaningful.

The consequence of these two problems was a dependent variable that did not correspond to a consistently defined measure of AI adoption. This was visible in the fitted intercept of the initial model, which implied a baseline AI adoption rate for large enterprises of roughly 62%, more than 20 percentage points above the actual Eurostat-published rate for large EU enterprises in the same period (41.2% in 2024; Eurostat, 2025a). The initial two-way fixed effects specification also produced a condition number on the order of 10^{15} , several orders of magnitude above the threshold conventionally treated as indicating severe multicollinearity. Investigation traced this to a second, independent issue: Digital STRI is fixed within each country across the sample period (it does not vary by year in the extract used), so once country fixed effects are included, STRI is a near-exact linear function of the country dummies, and its coefficient in that specification is not identified in any meaningful sense.

The correction applied here restricts the dependent variable to a single indicator (enterprises using AI technologies for at least one of the listed purposes) under a single, comparable denominator (percentage of all enterprises), and drops the two-way fixed effects specification in favor of models in which Digital STRI's main effect is actually identified (Section 3.4). This reduces the usable sample from 731 to 65 country–size–year cells. The reduction is driven by three compounding factors: restricting to one indicator and one unit removes roughly 88% of the original 731 rows by construction, since those rows represented eight other indicator–unit combinations, not genuinely independent observations; the retained indicator was fielded consistently only in 2023 and 2025, with partial 2024 coverage and no 2021 coverage, further reducing available cells; and two countries (Germany, Croatia) have incomplete coverage across size classes or years within the retained indicator.

We treat this as the correct trade-off. A specification with a larger N but an outcome variable that does not measure what it claims to measure does not produce more credible estimates; it produces estimates whose interpretation is not supported by the underlying measurement. The corrected sample of 65 observations still spans all ten countries and all three size classes, supports clustered standard errors at the country level, and, as

shown in Section 4, produces coefficient estimates that are internally consistent with independently published Eurostat aggregates, which the original 731-observation specification did not. We report both specifications in Section 4 so that the reader can see exactly what changed and why, rather than only the corrected numbers.

Econometric specification

The corrected model is estimated as:

$$AI_{cst} = \beta_0 + \beta_1 Small_s + \beta_2 Medium_s + \beta_3 STRI_c + \beta_4 (STRI_c \times Small_s) + \beta_5 (STRI_c \times Medium_s) + \beta_6 Cloud_{cst} + \varepsilon_{cst}$$

where c indexes countries, s enterprise size classes, and t survey years. Small and Medium are indicator variables for the 10–49 and 50–249 employee classes, respectively, with enterprises employing 250 or more workers serving as the reference category. STRI and Cloud are standardized (z-scored) continuous variables. Standard errors are clustered at the country level.

Two specifications are estimated on the corrected sample. Model 1 is a pooled specification without fixed effects. Model 2 adds year fixed effects to account for common changes in AI adoption across survey years. Country fixed effects are not included because the main explanatory variable, Digital STRI, is constant within country over the sample period.

Identification of the regulatory-intensity effect

Digital STRI does not vary within a country over the sample period. Consequently, a specification containing country fixed effects cannot separately identify the main effect of STRI because the variable is perfectly collinear with the country effects.

The original specification nevertheless included country and year fixed effects and reported a near-zero coefficient on STRI. That coefficient cannot be interpreted as evidence that regulatory intensity has no effect on AI adoption. Rather, the country fixed effects absorb the cross-country variation in STRI that is required to estimate its main effect.

The corrected specifications therefore omit country fixed effects and retain year fixed effects only in Model 2. This allows the cross-country variation in STRI to identify its main effect while controlling for common year-specific changes in AI adoption. The trade-off is that the estimated STRI effect is identified from only ten countries and may therefore reflect unobserved country characteristics correlated with regulatory restrictiveness. The estimates should consequently be interpreted as associations rather than causal effects.

Inference with few clusters

Both corrected models cluster standard errors at the country level, giving $G = 10$ clusters. Conventional cluster-robust standard errors rely on asymptotic approximations that become unreliable when the number of clusters is small and may result in downward-biased standard errors and overstated statistical significance (Cameron, Gelbach, & Miller, 2008). Cameron and Miller (2015) recommend using a t -distribution with $G - 1$ degrees of freedom as a minimum adjustment in settings with few clusters. With only ten clusters, we therefore supplement conventional cluster-robust inference with a $t(9)$ correction and a wild cluster bootstrap.

For the pooled model, we report three p-values for each coefficient: the conventional cluster-robust p-value, a p-value calculated using a $t(9)$ reference distribution, and a wild cluster bootstrap p-value. The bootstrap uses Rademacher sign weights and exact enumeration of all $2^{10} = 1,024$ possible sign-flip combinations across the ten country clusters. Exact enumeration is used rather than a simulated approximation because the number of clusters is sufficiently small to permit evaluation of the full permutation space.

Where the three inference procedures produce different conclusions, the disagreement is reported explicitly rather than selecting the method that produces the most favorable result. This is particularly important for the cloud-readiness coefficient, for which conventional and $t(9)$ -adjusted inference indicate statistical significance while the wild cluster bootstrap does not.

RESULTS

4.1 Descriptive statistics

Table 2 reports mean AI adoption, Digital STRI, and mean cloud readiness by country, pooling the available observations across enterprise-size classes and survey years in the corrected sample. Table 3 reports mean AI adoption by enterprise-size class.

The corrected sample shows substantial differences in AI adoption across countries. Finland has the highest mean adoption rate in the sample at 35.67%, followed by Austria at 32.26%, Belgium at 32.02%, and Denmark at 32.00%. At the lower end, Croatia and Romania report mean adoption rates of 12.29% and 6.18%, respectively. These differences are consistent with the broader differences reported in Eurostat's published enterprise AI statistics (Eurostat, 2025b).

Differences across enterprise-size classes are even more pronounced. Large enterprises, used as the reference category, have a mean AI adoption rate of 41.05%, compared with 21.24% for medium-sized enterprises and 11.68% for small enterprises. The descriptive statistics therefore show a clear size-based adoption gap before considering regulatory intensity and digital readiness.

Country	Mean AI adoption (%)	N	Digital STRI	Mean cloud readiness (%)
Finland	35.67	6	0.11	88.56
Austria	32.26	6	0.18	65.88
Belgium	32.02	6	0.22	71.87
Denmark	32.00	6	0.12	79.78
Netherlands	29.38	9	0.14	77.99
Sweden	27.40	6	0.13	82.47
Germany	25.46	5	0.20	67.70
France	20.05	6	0.28	52.46
Croatia	12.29	9	0.25	60.91
Romania	6.18	6	0.21	30.82

Table 2 Descriptive statistics by country, corrected sample.

Size class	Mean adoption (%)	SD	N
250+ employees (reference)	41.05	18.49	22
50–249 employees	21.24	12.88	22
10–49 employees	11.68	7.56	21

Table 3 Descriptive statistics by enterprise size class, corrected sample.

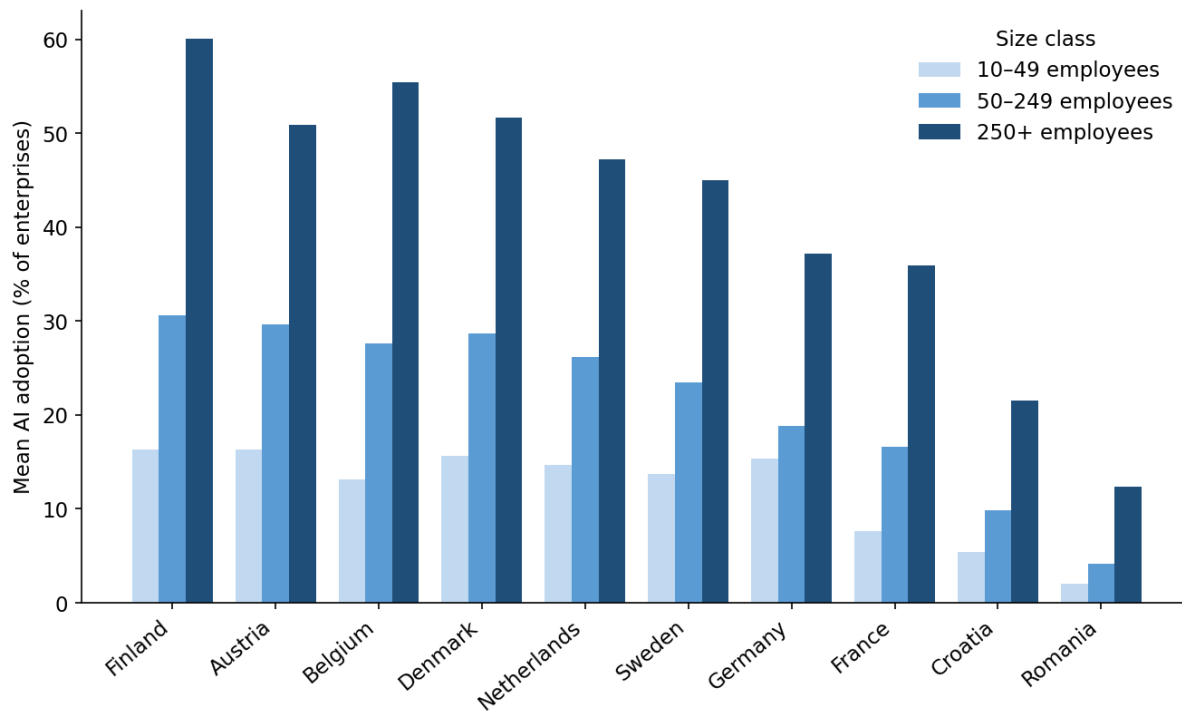


Figure 1 AI adoption by country and enterprise size class.

Preliminary specification (withdrawn)

Table 4 reports the preliminary specification estimated using the original 731-observation dataset described in Section 3.3. These estimates are presented only to document the original result and to show why the data and specification corrections described in Section 3 were necessary; they are not used to support the substantive conclusions of this study.

The preliminary pooled model produced relatively small coefficients and low explanatory power. The two-way fixed-effects specification produced a very large condition number, approximately 1.1×10^{15} , indicating severe numerical instability. More importantly, because Digital STRI is constant within countries, its main effect cannot be separately identified once country fixed effects are included. The near-zero STRI coefficient in the two-way fixed-effects model should therefore not be interpreted as evidence against the regulatory-intensity hypothesis.

Independent variable	Model 1: Pooled OLS	Model 2: Two-way FE (withdrawn)
Small (10–49), ref. 250+	-5.816* (3.145)	-5.167*** (1.777)
Medium (50–249), ref. 250+	-4.322*** (1.543)	-4.118*** (0.883)
Digital STRI (z)	-0.335 (1.880)	-0.039 (0.925)
STRI × Small	1.346 (1.515)	1.459 (1.390)
STRI × Medium	0.992 (1.069)	1.058 (1.034)
Cloud readiness (z)	2.067 (1.894)	2.543*** (0.965)
Country FE	No	Yes
Year FE	No	Yes
N	731	731

Independent variable	Model 1: Pooled OLS	Model 2: Two-way FE (withdrawn)
R ²	0.029	0.080
Condition number	7.87	$\approx 1.1 \times 10^{15}$

Table 4 Preliminary specification using the uncorrected sample (N = 731).

Notes: Withdrawn specification, reported for transparency only. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The near-zero coefficient on Digital STRI and its interaction terms in this specification, particularly the collapse of the STRI main effect to -0.039 under country fixed effects, is a consequence of the identification problem described in Section 3.5 rather than evidence that regulatory intensity has no relationship with AI adoption.

Corrected specification

Table 5 presents the corrected regression estimates based on the 65 observations retained after applying the data-selection criteria described in Section 3.3. Model 1 is the pooled specification, while Model 2 includes year fixed effects. Both models use standard errors clustered at the country level. Because Digital STRI takes only ten distinct country-level values, the STRI coefficients reported below, including the interaction terms discussed next, are identified from cross-sectional variation across these ten countries and should be interpreted with this constraint in mind.

The results show a substantial difference in AI adoption between enterprise-size classes. In the pooled model, small enterprises have an estimated adoption rate approximately 10.35 percentage points below the large-enterprise reference category, while medium-sized enterprises are approximately 10.66 percentage points lower. In the year-fixed-effects model, the corresponding differences are 14.39 and 12.45 percentage points. These estimates indicate a large size-based adoption gap in the corrected sample.

The coefficient on Digital STRI is negative in both models. However, the pooled-model estimate is not statistically significant under conventional cluster-robust inference. The interaction terms between Digital STRI and enterprise size are positive in both specifications. This indicates that the negative adoption difference between smaller enterprises and large enterprises becomes smaller as regulatory intensity increases.

Cloud readiness has a positive and relatively large coefficient in both specifications. In the pooled model, a one-standard-deviation increase in cloud readiness is associated with an estimated 12.47 percentage-point increase in AI adoption, while the corresponding estimate in the year-fixed-effects model is 10.04 percentage points. These estimates are statistically significant under conventional cluster-robust inference, although their robustness under the alternative small-cluster procedures is examined in Section 4.5.

The year-fixed-effects model also shows a substantial increase in AI adoption in 2025 relative to 2023, with an estimated increase of 14.20 percentage points. The 2024 coefficient is positive but not statistically significant.

Overall, the corrected specification indicates that enterprise size is strongly associated with AI adoption, while the relationship between regulatory intensity and adoption differs across firm-size classes. Because the corrected sample contains only ten country clusters, however, the conventional significance levels in Table 5 should be interpreted together with the additional inference checks presented in Section 4.5.

Independent variable	Model 1: Pooled OLS	Model 2: Year FE
Small (10–49), ref. 250+	-10.350*** (2.065)	-14.390*** (2.992)
Medium (50–249), ref. 250+	-10.655*** (1.107)	-12.446*** (1.979)

Independent variable	Model 1: Pooled OLS	Model 2: Year FE
Digital STRI (z)	-4.783 (3.567)	-5.545* (3.159)
STRI × Small	9.583*** (1.665)	8.722*** (2.083)
STRI × Medium	6.278*** (1.245)	5.701*** (1.522)
Cloud readiness (z)	12.469*** (2.528)	10.035*** (2.009)
Year 2024 (ref. 2023)	—	1.711 (2.415)
Year 2025 (ref. 2023)	—	14.204*** (2.332)
N	65	65
R ²	0.722	0.862
Adj. R ²	0.693	0.843
Condition number	6.52	6.65

Table 5 Corrected regression estimates (N = 65).

Notes: Model 1 is pooled OLS; Model 2 includes year fixed effects. Standard errors are clustered at the country level. Significance markers are based on conventional cluster-robust inference; small-cluster corrections are reported in Section 4.5. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

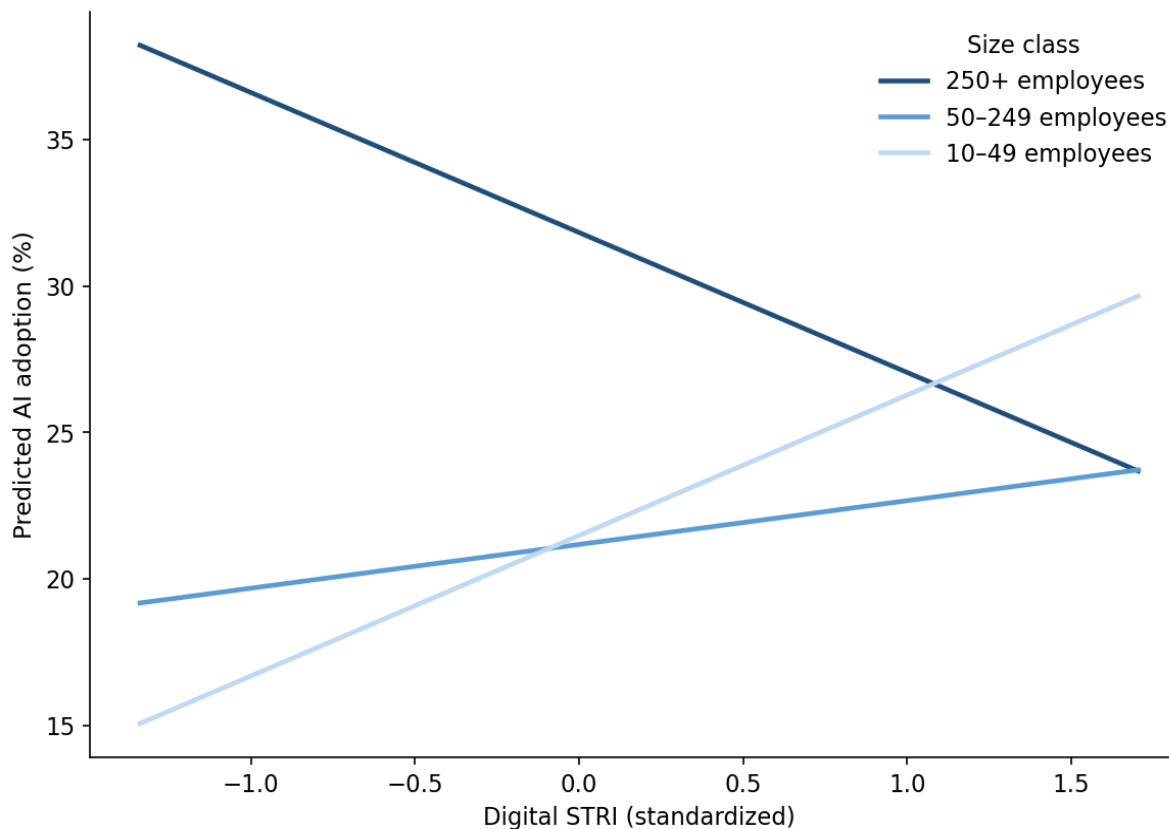


Figure 2 Predicted AI adoption by enterprise size across levels of Digital STRI.

Robustness checks

Table 6 reports variance inflation factors for the corrected pooled model. All reported VIF values are below 5, ranging from 1.00 to 3.24. The condition number is approximately 6.5, substantially lower than the value observed in the withdrawn specification. These results indicate that the corrected model does not exhibit the severe multicollinearity associated with the original specification.

Variable	VIF
Small (10–49)	1.41
Medium (50–249)	1.00
Digital STRI (z)	3.24
STRI × Small	2.07
STRI × Medium	2.04
Cloud readiness (z)	2.02

Table 6 Variance inflation factors, corrected pooled model.

Table 7 reports a leave-one-country-out jackknife of the corrected pooled model. The coefficient on the medium-enterprise indicator remains statistically significant regardless of which single country is excluded. The STRI × Small interaction also remains statistically significant across all country exclusions, while the cloud-readiness coefficient remains statistically significant throughout the jackknife exercise.

Excluded country	Small (p)	Medium (p)	STRI (p)	STRI×Small (p)	Cloud (p)
Austria	-10.42 (0.00)	-10.87 (0.00)	-4.69 (0.19)	9.60 (0.00)	12.52 (0.00)
Belgium	-11.06 (0.00)	-10.69 (0.00)	-6.26 (0.10)	10.14 (0.00)	10.95 (0.00)
Croatia	-8.62 (0.00)	-9.79 (0.00)	-1.07 (0.54)	8.69 (0.00)	14.38 (0.00)
Denmark	-10.46 (0.00)	-10.91 (0.00)	-4.82 (0.20)	9.77 (0.00)	12.50 (0.00)
Finland	-9.31 (0.00)	-9.79 (0.00)	-4.08 (0.27)	8.41 (0.00)	12.57 (0.00)
France	-11.12 (0.00)	-10.75 (0.00)	-7.14 (0.10)	10.98 (0.00)	11.32 (0.00)
Germany	-10.96 (0.00)	-11.01 (0.00)	-4.82 (0.19)	9.44 (0.00)	12.25 (0.00)
Netherlands	-10.77 (0.00)	-10.98 (0.00)	-5.06 (0.16)	9.60 (0.00)	12.26 (0.00)
Romania	-1.34 (0.86)	-6.97 (0.04)	-2.82 (0.48)	11.24 (0.00)	18.95 (0.00)
Sweden	-10.31 (0.00)	-10.38 (0.00)	-5.39 (0.14)	9.98 (0.00)	12.70 (0.00)

Table 7 Leave-one-country-out jackknife, corrected pooled model. Cell values are coefficients with p-values in parentheses.

The small-enterprise main effect is less stable. Its coefficient remains statistically significant when most individual countries are excluded, but when Romania is excluded, the coefficient falls from −10.35 to −1.34 and becomes statistically insignificant ($p = 0.86$). This indicates that the small-enterprise main effect is sensitive to

the inclusion of Romania.

The $\text{STRI} \times \text{Small}$ interaction does not show the same sensitivity. When Romania is excluded, the interaction coefficient increases from 9.58 to 11.24 and remains statistically significant. The interaction therefore appears more stable than the small-enterprise main effect within the corrected sample.

These jackknife results do not establish that Romania causes the observed size gap. They instead show that Romania has material influence on the estimated small-enterprise coefficient, while the relationship between regulatory intensity and firm size remains stable across the country exclusions.

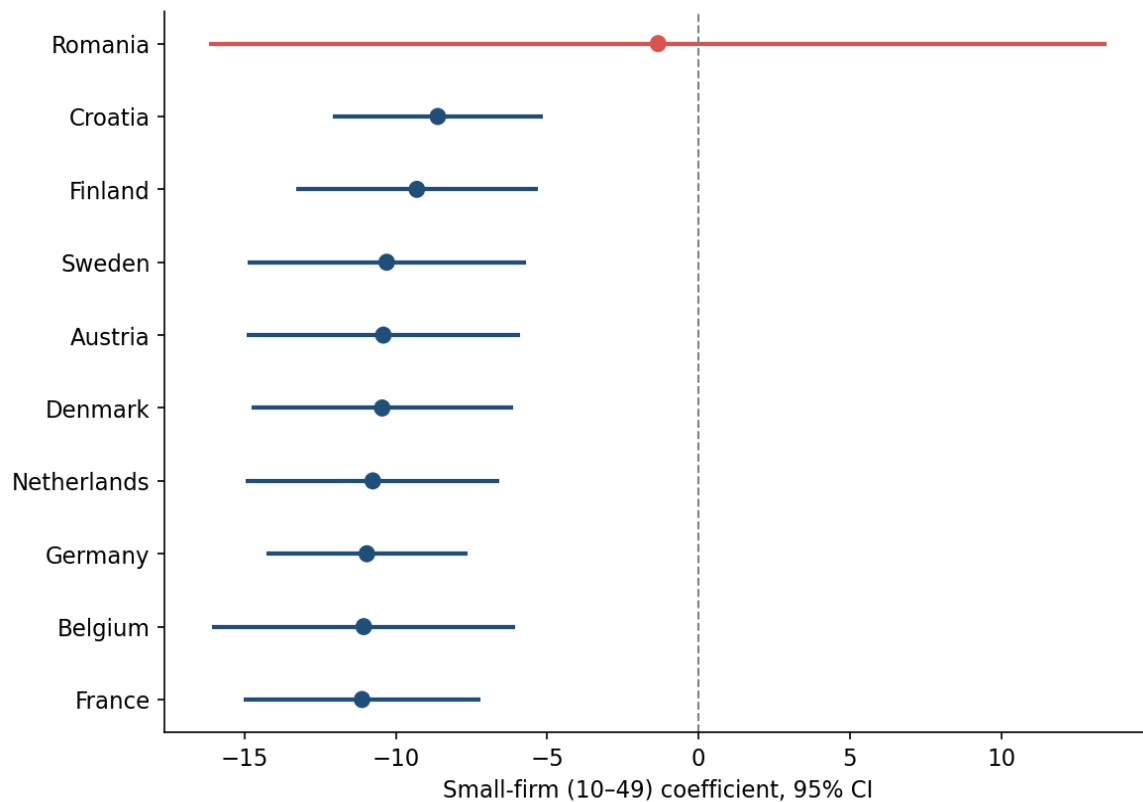


Figure 3 Leave-one-country-out jackknife estimates of the small-firm AI adoption gap.

Small-cluster inference

Table 8 compares three approaches to statistical inference for the pooled corrected model: conventional country-clustered p-values, p-values based on a $t(9)$ reference distribution, and wild cluster bootstrap p-values using Rademacher weights. The bootstrap evaluates all $2^{10} = 1,024$ possible sign-flip combinations across the ten country clusters.

Variable (Model 1)	Cluster-robust p	t(9) p	Wild bootstrap p
Small (10–49)	0.000	0.0007	0.0098
Medium (50–249)	0.000	0.0000	0.0020
Digital STRI (z)	0.180	0.2129	0.3145
STRI $\times$ Small	0.000	0.0003	0.0020
STRI $\times$ Medium	0.000	0.0007	0.0078

Variable (Model 1)	Cluster-robust p	t(9) p	Wild bootstrap p
Cloud readiness (z)	0.000	0.0008	0.1504

Table 8 Small-cluster inference comparison for the corrected pooled model.

Notes: Wild cluster bootstrap uses Rademacher weights and exact enumeration of all 1,024 possible sign-flip combinations across the ten country clusters.

The comparison changes how several of the results should be interpreted.

First, the $\text{STRI} \times \text{Small}$ interaction remains statistically significant under all three inference procedures, including the wild cluster bootstrap ($p = 0.002$). The interaction also remains statistically significant in every leave-one-country-out specification. This makes the finding that the small-enterprise adoption gap narrows as regulatory intensity increases one of the most consistently supported results in the analysis.

Second, the $\text{STRI} \times \text{Medium}$ interaction also remains statistically significant under all three inference procedures, with a wild-bootstrap p-value of 0.0078. This indicates that the relationship between regulatory intensity and AI adoption also differs for medium-sized enterprises relative to large enterprises.

Third, the main Digital STRI coefficient is not statistically significant under any of the three inference procedures in the pooled model. Its wild-bootstrap p-value is 0.3145. The results therefore do not provide evidence of a statistically significant direct relationship between regulatory intensity and enterprise AI adoption in the corrected sample.

Fourth, the cloud-readiness coefficient is statistically significant under conventional clustered inference and the $t(9)$ correction, but not under the wild cluster bootstrap. Its bootstrap p-value is 0.1504. The positive coefficient is therefore a consistent point-estimate pattern, but the available data do not provide sufficiently strong evidence to classify this relationship as robust under the most demanding small-cluster check.

Finally, the small-enterprise main effect remains statistically significant under the wild cluster bootstrap ($p = 0.0098$), but its sensitivity to the exclusion of Romania shown in Table 7 means that it should be interpreted with greater caution than the medium-enterprise coefficient or the $\text{STRI} \times \text{Small}$ interaction. The medium-enterprise coefficient is more stable because it survives both the bootstrap correction and every jackknife exclusion.

Taken together, the robustness checks provide the strongest support for two findings: the substantial AI-adoption gap between smaller and larger enterprises, particularly for medium-sized firms, and the positive interaction between regulatory intensity and firm size. The cloud-readiness relationship remains promising but should be treated as suggestive rather than conclusive given the small-cluster inference results.

DISCUSSION

5.1 The firm-size gap is the dominant finding, with one caveat

The results show a substantial difference in AI adoption between large enterprises and smaller firms. Across the corrected specifications, small and medium-sized enterprises have lower estimated adoption rates than large enterprises, with the medium-enterprise coefficient remaining statistically significant across the inference procedures and country-exclusion checks. The small-enterprise coefficient is also statistically significant under the wild cluster bootstrap, although the leave-one-country-out analysis shows that it is sensitive to the inclusion of Romania. These findings are consistent with the literature reviewed in Section 2.1, which identifies implementation costs, limited expertise, organizational capacity, and other resource constraints as important barriers to enterprise AI adoption.

The size gap suggests that differences in enterprise resources and capabilities remain important even within a broadly shared European institutional environment. Large enterprises may have greater capacity to finance technological investment, acquire specialized skills, and integrate AI into existing business processes. The results therefore support the view that enterprise characteristics should be considered when evaluating national differences in AI adoption rather than treating adoption as a uniform country-level outcome.

However, the results should not be interpreted as evidence that firm size alone determines whether an enterprise adopts AI. The variation within the firm-size categories and the sensitivity of the small-enterprise coefficient to Romania indicate that other country- and firm-level factors also contribute to adoption differences.

5.2 Cloud readiness: a large but fragile estimate

Cloud readiness has a large positive coefficient in both corrected specifications. A one-standard-deviation increase in the share of enterprises using basic paid cloud computing services is associated with an estimated increase in AI adoption of approximately 10 to 12 percentage points. This direction is consistent with the literature reviewed in Section 2.2, which suggests that digital infrastructure can provide an important foundation for the deployment of more advanced technologies.

The result is nevertheless less conclusive than the firm-size and regulatory-interaction findings. Cloud readiness remains statistically significant under conventional cluster-robust inference and the $t(9)$ correction, but its significance disappears under the wild cluster bootstrap. This difference is important because the small number of country clusters makes conventional significance levels less reliable.

The appropriate interpretation is therefore that cloud readiness is **positively associated with AI adoption in the estimated models, but the available sample does not provide sufficiently strong evidence to classify this relationship as robust under the strictest inference procedure used in the study**. The result remains theoretically plausible and consistent with the broader literature, but larger samples and additional observations are needed to establish the relationship more firmly.

5.3 Regulatory intensity: a conditional effect that survives the strictest test available

The results provide no statistically significant evidence of a direct relationship between Digital STRI and enterprise AI adoption. The main STRI coefficient is not statistically significant under the alternative inference procedures used in the pooled model. This means that the study does not find support for the hypothesis that higher digital-services regulatory restrictiveness is systematically associated with lower enterprise AI adoption across the selected countries.

The interaction terms, however, produce a different result. Both the $\text{STRI} \times \text{Small}$ and $\text{STRI} \times \text{Medium}$ coefficients are positive and remain statistically significant under conventional clustered inference, the $t(9)$ correction, and the wild cluster bootstrap. The leave-one-country-out analysis also shows that the $\text{STRI} \times \text{Small}$ interaction remains statistically significant when any individual country is excluded.

The positive interaction means that the negative adoption gap between smaller enterprises and large enterprises becomes narrower as Digital STRI increases. In other words, the relationship between regulatory intensity and AI adoption is conditional on enterprise size rather than uniform across firms. This result runs contrary to the simple compliance-cost expectation developed from the data-localization literature, under which more restrictive regulation would be expected to impose a greater burden on firms with fewer resources.

Several explanations are possible, but the data cannot distinguish among them. First, Digital STRI is a broad measure of digital-services trade restrictiveness and does not specifically measure AI regulation or data localization. The interaction may therefore capture differences in wider digital regulatory environments rather than the specific compliance mechanism described in the India case. Second, countries with higher STRI scores may also implement other policies supporting SME digitalization, meaning that the interaction could reflect a broader policy environment rather than the effect of regulatory restrictiveness itself. Third, because STRI

provides only ten distinct country-level values in the sample, the interaction is identified from limited cross-country variation.

The stability of the interaction under the jackknife analysis reduces concern that the result is being driven entirely by one country within the sample. However, this stability should not be interpreted as evidence of causality. The most appropriate conclusion is that **the relationship between regulatory intensity and AI adoption differs across enterprise-size classes in this sample, with the estimated adoption gap narrowing as regulatory intensity increases.**

5.4 Romania as a structurally distinct case

Romania represents an important qualification to the interpretation of the firm-size results. It has the lowest mean AI adoption rate in the corrected sample and is the only country whose exclusion causes the small-enterprise coefficient to become statistically insignificant. At the same time, excluding Romania does not weaken the STRI × Small interaction; instead, the estimated interaction coefficient increases.

This suggests that the small-enterprise main effect is influenced by the presence of a particularly low-adoption country, while the interaction between regulatory intensity and firm size is more stable across the sample. Romania should not therefore be treated as an outlier to be removed simply because it affects the results. Its relatively low level of adoption represents genuine cross-country variation that is relevant to the research question.

The result also highlights the importance of country heterogeneity when interpreting enterprise AI adoption. Differences in digital development, infrastructure, institutional capacity, and firm characteristics may produce adoption patterns that are not fully captured by the variables included in the current specification. The ten-country sample is therefore useful for identifying patterns within the selected countries, but it is not sufficient to establish that the same relationships would hold across the entire European Union.

CONCLUSION AND POLICY IMPLICATIONS

This study examined whether firm size, digital infrastructure readiness, and regulatory intensity are associated with differences in enterprise AI adoption across ten selected European Union member states. After correcting the original data construction problem and applying inference procedures appropriate for the small number of country clusters, the results provide several important findings.

First, enterprise size is strongly associated with AI adoption. Small and medium-sized enterprises have substantially lower adoption rates than large enterprises across the corrected specifications. The medium-enterprise gap is particularly stable across the robustness checks, while the small-enterprise coefficient is statistically supported by the wild cluster bootstrap but is sensitive to the exclusion of Romania. This finding reinforces the importance of firm-level resources and capabilities in explaining differences in AI adoption.

Second, cloud readiness has a large positive association with AI adoption in both corrected specifications. However, this relationship does not remain statistically significant under the wild cluster bootstrap. The evidence therefore suggests an important role for basic digital infrastructure, but it is not sufficiently strong in this sample to describe cloud readiness as a robust determinant of AI adoption.

Third, the results do not provide evidence of a statistically significant direct relationship between Digital STRI and enterprise AI adoption. The main regulatory-intensity coefficient is not statistically significant under the small-cluster inference procedures used in the study. At the same time, the interaction between regulatory intensity and enterprise size is consistently positive and statistically significant. The estimated negative adoption gap between smaller enterprises and large enterprises therefore becomes narrower as Digital STRI increases. This result does not support the simple expectation that greater regulatory restrictiveness necessarily produces a larger disadvantage for smaller firms.

The interaction result should nevertheless be interpreted cautiously. Digital STRI is a broad measure of digital-services trade restrictiveness rather than an AI-specific regulatory measure, and the analysis is based on only ten countries. The study therefore cannot establish why the interaction is positive or whether the relationship is causal. It may reflect differences in broader digital-policy environments, SME support measures, or other country characteristics that are correlated with regulatory intensity.

From a policy perspective, the findings suggest that efforts to reduce differences in enterprise AI adoption should pay particular attention to the conditions facing smaller firms. Improving access to digital infrastructure, technological capabilities, and the resources required for AI implementation may help address the substantial adoption gap between SMEs and large enterprises. However, the cloud-readiness result should be treated as suggestive rather than conclusive given the small-cluster inference results.

The findings also provide no empirical basis in this sample for arguing that simply reducing regulatory intensity would increase enterprise AI adoption. Instead, the significant interaction between regulatory intensity and firm size suggests that the relationship between regulatory conditions and adoption may depend on enterprise characteristics and the wider policy environment. Policymakers should therefore avoid interpreting regulatory restrictiveness in isolation and should consider whether regulatory frameworks are accompanied by measures that strengthen firms' capacity to comply with and benefit from digital technologies.

These conclusions are limited to the ten EU member states and the corrected 2023–2025 analytical period examined in this study. They should not be generalized directly to other regulatory environments or to the UAE, Singapore, China, or India cases discussed in the literature review. The small number of countries, incomplete panel coverage, broad measurement of regulatory intensity, and observational nature of the analysis all limit the strength of the conclusions. Nevertheless, the findings provide evidence that firm size remains an important dimension of the enterprise AI adoption divide and that the relationship between regulatory intensity and adoption is more complex than a uniform negative effect.

Limitations And Future Research

Several limitations should be considered when interpreting the findings of this study.

Sample size and number of clusters. The corrected sample contains 65 observations across ten countries, three enterprise-size classes, and the available survey years. With only ten country clusters, conventional cluster-robust inference may be unreliable. This study addresses this issue by reporting $t(9)$ -adjusted and wild cluster bootstrap p-values alongside conventional estimates. However, no statistical correction can eliminate the underlying limitation imposed by the small number of countries. The results should therefore be interpreted as evidence within the selected sample rather than as broadly generalizable estimates.

Panel balance and time coverage. The corrected AI-adoption indicator is not available for every country, enterprise-size class, and survey year. In particular, the retained indicator is available consistently in 2023 and 2025, with partial coverage in 2024, while the relevant indicator is not available in 2021. Germany and Croatia also have incomplete country-year-size coverage. The dataset is therefore better characterized as an unbalanced repeated cross-section than as a balanced panel, limiting the ability to examine within-country changes over time.

Measurement of regulatory intensity. Digital STRI is a broad measure of restrictions affecting digital services and is not designed specifically to measure AI regulation or data localization. Because the index is constant within each country over the study period, its effect is identified from cross-country variation across only ten countries and cannot be estimated together with country fixed effects. Future research would benefit from an AI-specific measure of regulatory intensity or data-governance restrictiveness.

Endogeneity and interpretation. The analysis identifies associations rather than causal effects. Regulatory intensity, cloud readiness, and broader national digital capabilities may be correlated with other country characteristics that are not fully captured by the model. In addition, the study does not include an instrumental variable or another identification strategy capable of addressing potential endogeneity.

Country-specific influence. The leave-one-country-out analysis indicates that the small-enterprise main effect is sensitive to the exclusion of Romania, whereas the $\text{STRI} \times \text{Small}$ interaction remains statistically significant. This suggests that some conclusions are more sensitive to sample composition than others. Romania is therefore retained because excluding a country solely because it influences the results would introduce a different form of selection bias.

Future Research

Future research could address these limitations by expanding the analysis to a larger set of EU member states and incorporating additional survey waves as comparable AI-adoption indicators become available. A larger number of country clusters would improve the reliability and generalizability of the statistical inference. Further research should also consider regulatory measures that are more directly related to AI governance, data localization, and data-transfer restrictions rather than relying solely on the broader Digital STRI.

Additional firm-level data could further improve the analysis by distinguishing factors such as firm productivity, industry, digital skills, investment capacity, and prior technology adoption. This would allow researchers to investigate more directly why smaller enterprises adopt AI at substantially lower rates and whether the regulatory-intensity interaction identified in this study persists after accounting for a wider range of firm and country characteristics.

Finally, future studies could examine whether the relationship between regulatory intensity and firm size differs across sectors and over time. Such evidence would help determine whether the interaction observed in this study reflects a broader feature of European enterprise AI adoption or a pattern specific to the countries and period examined here.

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Data Availability Statement: The data used in this study are publicly available from Eurostat's Community Survey on ICT Usage in Enterprises (dataset isoc_eb_ai) and the OECD Digital Services Trade Restrictiveness Index (Digital STRI) database. The data-cleaning and analysis code is available from the corresponding author upon reasonable request.

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