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DIGITAL CAPABILITY AND AI ADOPTION IN MEDIUM-SIZED ENTERPRISES IN THE EU

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Abstract: *Adoption of AI varies across the EU, even though the differences in ICT training and employment of ICT specialists are smaller. This shows that the simple presence of digital resources does not ensure the effective integration of the artificial intelligence into enterprises' processes. The study analyses the relation between digital capability and AI adoption in medium-sized enterprises in the EU. Digital capability is evaluated through two elements: employee training in ICT and the employment of ICT specialists. Romania's position is also analysed separately. The analysis uses Eurostat data for 2024 on enterprises with 50–249 employees. The main sample included 26 EU Member States. Descriptive statistics, Pearson correlations and five linear regression models were used. Diagnostic and sensitivity checks were also performed, and countries were grouped descriptively according to their digital profile. Romania's position was evaluated by comparing it with European averages, indicator rankings and the values estimated by the main model. Both ICT training and employment of ICT specialists are positively correlated with AI adoption. The connection is stronger for employee training, with a correlation coefficient of r =0.708, compared to r =0.642 for ICT* *specialists. When the two variables are analysed together, training remains statistically significant (B=0.418, p=0.023), while ICT specialists are no longer significant (B=0.273, p=0.225). The sample explains 53.3% of differences between countries. Romania has an AI adoption rate of 3.88%, the lowest in the sample The results show that the development of digital skills among employees is more closely connected to the adoption of AI than the simple employment of ICT specialists. Technical expertise remains important but is more effective when supported by constant employee training. Because the analysis uses aggregated data for a single year, the results indicate associations across countries, but do not demonstrate causal relationships.*

JEL classification: M15, O33, J24, M53

Keywords: using AI in medium-sized enterprises; employee ICT training and AI adoption; employment of ICT specialists in organizations; organizational digital capability in Europe; cross-country differences in artificial intelligence adoption; digital transformation in the EU countries; Eurostat data on enterprise AI adoption; Romania's position in artificial intelligence adoption.

1. INTRODUCTION

Artificial intelligence (AI) has become an increasingly used component in organizational processes. In addition to automating repetitive tasks, AI systems can organize information, propose alternatives, and support some routine decisions (Shrestha et al., 2019; Trocin et al., 2021). The question now is not only if these tools are available to organizations, but why some organizations use them more than others.

In 2024, there were large differences between European Union countries. The percentage of medium-sized enterprises using at least one artificial intelligence technology was from 3.88% to 40.92%. The differences regarding ICT training and the employment of ICT specialists were smaller. This shows that the very existence of digital resources does not mean that artificial intelligence is used effectively.

Based on the literature, three key concepts help explain this discrepancy: the RBV, AMO, and digital transformation. The first one, the resource-based perspective, highlights that skills and knowledge are formed within the company (Arroyabe et al., 2024; Barney, 1991; Sánchez-

Rodríguez et al., 2025). The second is the Ability-Motivation-Opportunity (AMO) model, which shows us that skills only produce results when employees are motivated and have the necessary conditions to apply them (Blumberg & Pringle, 1982; Bos-Nehles et al., 2023). And the third concept, the literature on digital transformation, details that technology must be integrated into organizational processes, roles, and routines, not just adopted without bringing performance (Ammirato et al., 2023; Hanelt et al., 2020).

In fact, companies can develop skills of existing employees or can employ ICT specialists. The two strategies involve different resources, terms and risks (Autor, 2024; Muehlemann, 2025). However, studies do not sufficiently compare their distinct contributions, especially in the case of medium-sized enterprises, which have fewer resources than large corporations but more complex structures than small companies.

The current study aspires to respond to three research questions:

RQ1. To what extent is employee ICT training associated with AI adoption?

RQ2. To what extent is the employment of ICT specialists associated with AI adoption?

RQ3. Which of the two components maintain their association when analysed together?

The analysis uses data from Eurostat for the year 2024 and has the European Union Member State as the unit of analysis. Enterprises with number of employees between 50 and 249 are investigated, using descriptive statistics, Pearson correlations, five linear regression models, robustness checks, and a descriptive classification of national digital profiles. As the data are aggregated and cross-sectional, the results describe associations between countries, not causal relationships at the firm level.

The primary contribution of this study consists in separating two components which are often carried together under the label of digital capability, namely the training of employees in ICT and the employment of ICT specialists. The study shows that this differentiation matters for a better understanding of AI adoption and complements the European analysis by examining Romania's position separately.

2. LITERATURE REVIEW

Digital transformation is a socio-technical process in which technology, people and the way a company is organized are constantly changing together. Therefore, the adoption of AI cannot be explained only by the simple existence of technological tools integrated at the company level. Employee skills, managerial support and the integration of technology into current activity play an equally important role (Ammirato et al., 2023; Directorate-General for Research and Innovation, 2022). The national context influences this process through which culture, institutions and management practices shape the way in which companies understand change and invest in digital skills (Cayrat & Boxall, 2023; Festing & Proff, 2025; Sanders & De Cieri, 2021). Cross-country analysis is relevant in this given context, and the results should be analysed as contextual disparities rather than uniform characteristics of all companies in a given country (Komatsu et al., 2026).

2.1 AI in between decisions and organizational change

In medium-sized enterprises, the adoption of AI technologies can change the organization of work, job design, the way information flows, and the entire decision-making process (Glikson & Woolley, 2020; Graetz & Michaels, 2018; Kellogg et al., 2020; Úbeda-García et al., 2025). In the case of human resources, for example, AI can support recruitment, planning, and evaluation processes. However, its value counts on how it is integrated into existing responsibilities and processes. AI-based systems can analyse the data they have access to in real time and provide useful information for making personnel decisions. The benefits of implementation become more likely when employees come to understand the tools and find them useful, and also receive support to use them (Malik et al., 2023; Úbeda-García et al., 2025). Technology, within a company, can support flexibility and innovation, but it also cannot alone compensate for poorly defined processes or lack of employee skills.

At the managerial level, adopting AI technologies that can rapidly process large volumes of data can also help organizations observe and assess market changes faster than humans can (Enholm et al., 2022; Keding, 2020; Wamba et al., 2020). For mid-sized enterprises, the advantage lies not only in speed, but also in the ability to convert data and information into an organizational response that is reflected in the company's strategy.

Generative AI can easily integrate information from different sources, synthesize it, and provide managers with more options to support strategic decisions (Taksi Deveciyan et al., 2026). The technology should not be seen as a substitute for human experience and judgment, but rather, they become even more important and are valued when information is incomplete, the situation is difficult to interpret, or the decision can have significant effects on the organization and employees (Ramachandran et al., 2023; Shrestha et al., 2019).

Human-AI systems collaboration is more effective when the results provided by the technology can be understood, and users have the opportunity to analyze them and provide feedback. Trust in these systems increases when their functioning is clearly explained and when the responsibilities of humans and technology are clearly defined. At the same time, collaboration between specialists who know the field of activity and technical experts is essential for the algorithmic results to be interpreted correctly and transformed into relevant decisions for the organization (Adadi & Berrada, 2018; Berretta et al., 2023; Machucho & Ortiz, 2025; Seeber et al., 2020).

For this reason, the performance of an AI system cannot be evaluated only by the accuracy of the model or the speed with which it processes data. For organizations, it is equally important to observe whether the use of technology improves current work, supports better decision-making, and establishes a clear division of responsibilities between people and systems (Dwivedi et al., 2021; Enholm et al., 2022; Shrestha et al., 2019).

2.2 Digital capability

The resource-based view (RBV) explains why companies using similar technological tools can achieve different results. General AI tools can be bought or imitated relatively easily, but internal data, operational experience and skills developed over time are more difficult to transfer. The advantage arises not from the simple access to the technology, but from the way it is integrated with solely the organization's own resources (Arroyabe et al., 2024; Barney, 1991; Sánchez-Rodríguez et al., 2025).

Dynamic capabilities theory (Teece et al., 1997) reinforces this illustration, showing that resources can create value when companies manage to combine, adapt and integrate them into the organization's processes. From this perspective, the adoption of AI should not be seen as a technical investment, but as part of a process involving learning and reorganization for the entire organization. Innovation capability supports the testing of ideas and process change, while digital capability reflects the organization's ability to use digital resources to achieve its goals; together, they explain why some firms integrate AI into their current activities, while others remain at a limited or formal level of use (Arroyabe et al., 2024; Sánchez-Rodríguez et al., 2025).

The AMO model brings the role of employees to the forefront, starting with the idea that the mere existence of skills is not enough. For skills to be valued, people must be motivated and have the conditions that allow them to use them effectively; thus, ability concerns the necessary skills, motivation, and willingness to make an effort, and opportunity concerns the framework provided by the organization (Blumberg & Pringle, 1982; Bos-Nehles et al., 2023). In practice, IT support, autonomy, and knowledge sharing can make the difference between skills that remain at the individual level and those that are valued in the organization's work (Kettinger et al., 2015; Knies & Leisink, 2014).

Digital skills help employees not only for use AI technologies, but also to accept it more easily. People trust these systems more when they understand how they work, believe the results are fair, and feel in control of their work and decisions (Piotrowski & Revtiuk, 2026). That is why the training provides both technical knowledge and greater safety in using new technologies.

Companies can increase their digital capability by training the employees they have or by employing ICT specialists. Both options address to different needs, as ICT specialists' collaboration provides access to knowledge, while training improves the organization's ability to use technology. The current literature shows that the adoption of artificial intelligence depends on both components and cannot count exclusively on a small group of experts (Brey & Van Der Marel, 2024; Muehlemann, 2025).

At the same time, skills development is not the sole responsibility of the human resources department, but requires collaboration between management, technical teams, employees and educational institutions (Bukartaite & Hooper, 2023). Training programs and public policies can support this collaboration, especially in the case of companies that do not have the resources to build all the expertise they need in-house (Muehlemann, 2025).

2.3 Acceptance, trust and responsible use

The adoption of AI also changes the way that control is shared within the company. The algorithmic systems can support recruitment, task distribution, and performance evaluation. Their effectiveness shall be analysed in terms of the effects on how people work and on employees' experiences (Goods et al., 2019; Kinowska & Sienkiewicz, 2023).

Risks in AI technology adoption can appear when rules are set too strictly or when the level of monitoring increases. In these cases, employees may see technology as a control mechanism and a source of insecurity, rather than support in their work (Bukartaite & Hooper, 2023; Ouzian, 2024).

User autonomy and the option to provide feedback are important for the acceptance of new technologies into an organization. The system recommendations can help employees to work more effectively when they have the opportunity to choose and to use their own judgment. Contrarily, repetitive tasks and lack of explanations can reduce satisfaction and increase resistance to new technologies (Felstead et al., 2019; Mendonça et al., 2023; Ouzian, 2024).

Organizations must also protect employee data, ensure information security, and respond to their fears of job loss (Úbeda-García et al., 2025). Although these topics are not directly analysed in this study, they may explain why countries with similar levels of digital skills have different AI adoption rates.

2.4 Conceptual framework

The Technology Acceptance Model (TAM) highlights the user's perceived usefulness and ease of use of the system (Davis, 1989), while organizational adoption also depends on resources, processes and the national context. Therefore, the study combines a competency perspective with an organizational integration perspective. Based on the RBV (Barney, 1991), dynamic capabilities (Teece et al., 1997), and the AMO model (Bos-Nehles et al., 2023), both ICT training and the employment of ICT specialists should be positively associated with the AI adoption. However, the two variables depend on different mechanisms: staff training reflects the spread of skills within the organization, while collaboration with specialists reflects the concentration of technical expertise. The analysis of the two indicators allows for the examination of their specific contribution. The study does not directly test psychological mechanisms or internal processes and does not formulate causal conclusions. It rather examines whether one of the indicators retains its association after statistically controlling for the other.

3. METHODOLOGY

The study uses a quantitative, comparative and cross-sectional approach and focuses on medium-sized enterprises with 50–249 employees. The analysis looks at the relation between digital capability and the use of artificial intelligence in the year 2024.

Digital capability of the organizations is analysed through two indicators: the percentage of enterprises that provide employees ICT training and the rate of those that use ICT specialists. The first indicator shows how widespread digital training is within companies, and the second reflects access to specialized expertise. Recruitment difficulties are treated separately, as they depend not only on the need for skills, but also on the availability of vacancies and the labour market situation. The recruitment indicator should not be taken as a direct measure of the overall shortage of ICT skills. It also depends on whether enterprises had vacancies and attempted to recruit ICT specialists, which makes its underlying mechanism different from those of the training and specialist-use indicators.

The data comes from four Eurostat (Eurostat, n.d.) sets, drawn on 21 July 2026 and updated on 15 June 2026. All indicators refer to the year 2024 and to enterprises with 50–249 employees in NACE Rev. 2 sectors included in the ICT use survey. Agriculture, forestry, fishing, extractive industries and the financial sector are not part of the analysis. The values may be revised later by Eurostat.

Table 1. *Operationalization of variables and sources. Source: Authors' contribution based on Eurostat.*

Indicator	Role in analysis	Measurement	Eurostat dataset	Official name of the indicator
Adoption of AI	Dependent variable	Percentage of medium-sized enterprises that used at least one of the eight AI technologies included in the indicator in 2024	isoc_eb_ai	Enterprises using at least one of the AI technologies: AI_TTM, AI_TSR, AI_TNLG, AI_TIR, AI_TML, AI_TPA, AI_TAR, E_AI_TPVSG
ICT training	Main predictor	Percentage of medium-sized enterprises that provided employees with training to develop ICT skills	isoc_ske_itts	Enterprise provided training to their personnel to develop their ICT skills
ICT specialists	Main predictor	Percentage of medium-sized enterprises that have employed ICT specialists	isoc_ske_itspe	Enterprise employed ICT/IT specialists (reduced comparability with 2007)

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Recruitment difficulties	Additional predictor	Percentage of medium-sized enterprises that reported hard-to-fill positions for ICT specialists	isoc_ske_itrcrs	Enterprise had hard-to-fill vacancies for jobs requiring ICT specialist skills (reduced comparability with 2007)

Data availability led to the construction of three samples. The main sample includes 26 countries and excludes Portugal. The recruitment difficulties analysis includes 26 countries, with Portugal included and France excluded. The exploratory model uses the 25 countries with complete data for all three predictors. Missing values were not imputed.

***Table 2**. Construction of the analysed samples. Source: Authors' own elaboration.*

Analytical sample	Included variables	Models used	Number of states	Excluded states	Reason for exclusion
Main sample	ICT training, ICT specialists and AI adoption	M1, M2 and M3	26	Portugal	Values for training and ICT specialists were not available
Analysis of recruitment difficulties	Recruitment difficulties and AI adoption	M4	26	France	The value for recruitment difficulties was not available.
Exploratory model	ICT training, ICT specialists, recruitment difficulties and AI adoption	M5	25	Portugal and France	There was no complete data for all four variables simultaneously

For Sweden, Eurostat reports series breaks in all three indicators. These limit comparisons over time, but do not prevent cross-sectional analysis for 2024, so the observations have been retained. Each country has the same weight in the models, regardless of the size of the economy. Each country entered the analysis once and was treated as an independent observation. Possible regional dependence between EU Member States was not explicitly modelled.

Variables are expressed in percentage points. Unstandardized coefficients indicate the estimated difference in AI adoption associated with a one percentage point difference in the predictor, with other variables held constant. OLS regression models were estimated in Microsoft Excel 16.110.2 using the Analysis ToolPak. Additional diagnostic statistics, influence measures and HC3 robust standard errors were calculated in the analysis workbook using explicit formulas. Tests are two-tailed, and the significance level is 5%.

The analysis included descriptive statistics, Pearson correlations, five OLS linear regression models, and a median-based descriptive classification of countries. Coefficients, standard errors, t and p values, 95% confidence intervals, R^2, adjusted R^2, and F-test are reported. Model M3 is the main model; M5 is exploratory. Given the limited number of country-level observations, the models were intentionally kept parsimonious. Adding a large number of control variables would reduce statistical precision and increase the risk of overfitting.

Table 3. *Synthesis of regression models, Source: Authors' own elaboration.*

Model	Dependent variable	Predictor(s)	Analytical sample	Scope
M1	Adoption of AI	ICT training	26 states; Portugal excluded	Analyses the relation between ICT training and AI adoption
M2	Adoption of AI	ICT specialists	26 states; Portugal excluded	Analyses the relation between the employing specialists and adoption of AI
M3	Adoption of AI	ICT training; ICT specialists	26 states; Portugal excluded	Estimates the distinct contribution of each component, holding the other constant; main model
M4	Adoption of AI	Recruitment difficulties	26 states; France excluded, Portugal included	Analyses the relation between difficulties in recruiting ICT specialists and the adoption of AI
M5	Adoption of AI	ICT training; ICT specialists; recruitment difficulties	25 states; Portugal and France excluded	Explores the simultaneous contribution of the three predictors; interpreted with vigilence because of the small sample size and different reference population

Note: All models were estimated using OLS. M3 is the main model and M5 is exploratory. Each model uses only the complete observations for the included variables.

Analyses the relation between the employment of specialists and adoption of AI

For the descriptive analysis, countries were divided by medians of ICT training (40.14%) and ICT specialist use (41.94%). Four profiles emerged: consolidated digital ecosystem, development through internal training, reliance on specialized expertise, and limited digital capability. This classification is not a cluster analysis and does not test for differences between groups.

The main regression model was verified by several tests. Multicollinearity was analysed using the variance inflation factor. The linearity and correctness of the model shape were verified by scatterplots and the Ramsey RESET test.

Normality of residuals was checked by Shapiro–Wilk and Jarque–Bera tests, and equality of variance of residuals was analysed by Breusch–Pagan and White tests.

Plots for residuals and influential observations are presented in Appendix A. Potentially unusual observations were analysed using externally studentized residuals, leverage values, Cook distance, and the DFFITS indicator. The values for each country are shown in Table A1.

To check the stability of the results, the main model was re-estimated after removing certain observations and using HC3 robust standard errors. However, the main interpretation is based on the full sample. The graphs are shown in Appendix A, and the values for each country can be found in Table A1.

4. RESULTS

The analysis begins with a presentation of the main indicators and the relationships between them, continues with the results of the regression models and robustness checks, and then compares the digital profiles of the states and examines more closely the position of Romania in the European context.

4.1 Descriptive statistics

The AI adoption varies across the EU states from 3.88% to 40.92%, with an average of 21.30%. The average ICT training is 40.76%, and the average ICT specialist utilization is 43.18%. In the corresponding sample, 11.04% of enterprises report difficulties in filling positions requiring ICT specialists.

Table 4. *Descriptive statistics. Source: Authors' contribution based on Eurostat data.*

Description	N	Mean	Median	SD	Minimum	Maximum
ICT training (%)	26	40.76	40.14	12.06	17.15	62.25
ICT specialists (%)	26	43.18	41.94	9.42	22.24	58.43
AI adoption (%)	26	21.30	18.13	9.81	3.88	40.92
Recruitment difficulties (%)	26	11.04	9.17	5.45	3.30	27.60

Note: Statistics for ICT training, ICT specialist employment, and AI adoption refer to the main 26-country sample, with Portugal excluded. Statistics for recruitment difficulties refer to the separate 26-country recruitment sample, with France excluded and Portugal included.

The differences between countries are greater for AI adoption than for the two components of digital capability. The ratio of the maximum to the minimum value is 10.5 for AI adoption, compared to 3.6 for training and 2.6 for specialists. The average for AI adoption is above the median, which shows the influence of a few countries with high values.

4.2 Correlations between indicators

The ICT training and the employment of ICT specialists are positively associated with AI adoption. The association is stronger for ICT training ($r=0.708$, $p < 0.001$) than for ICT specialists ($r=0.642$, $p < 0.001$). The two predictors are also strongly correlated one with each other ($r=0.737$, $p < 0.001$). The recruitment difficulties have a moderate positive association with the AI adoption ($r=0.528$, $p=0.006$).

***Table 5.** Pearson correlations. Source: Authors' contribution based on Eurostat data.*

Relationship	N	Pearson	t	p
ICT Training and AI Adoption	26	0.708	4.91	< 0.001
ICT Specialists and AI Adoption	26	0.642	4.10	< 0.001
ICT Training and ICT Specialists	26	0.737	5.33	< 0.001
Recruitment Difficulties and AI Adoption	26	0.528	3.04	0.006

Note: Correlations involving ICT training and ICT specialist employment refer to the main 26-country sample, with Portugal excluded. The correlation between recruitment difficulties and AI adoption refers to the separate 26-country recruitment sample, with France excluded and Portugal included.

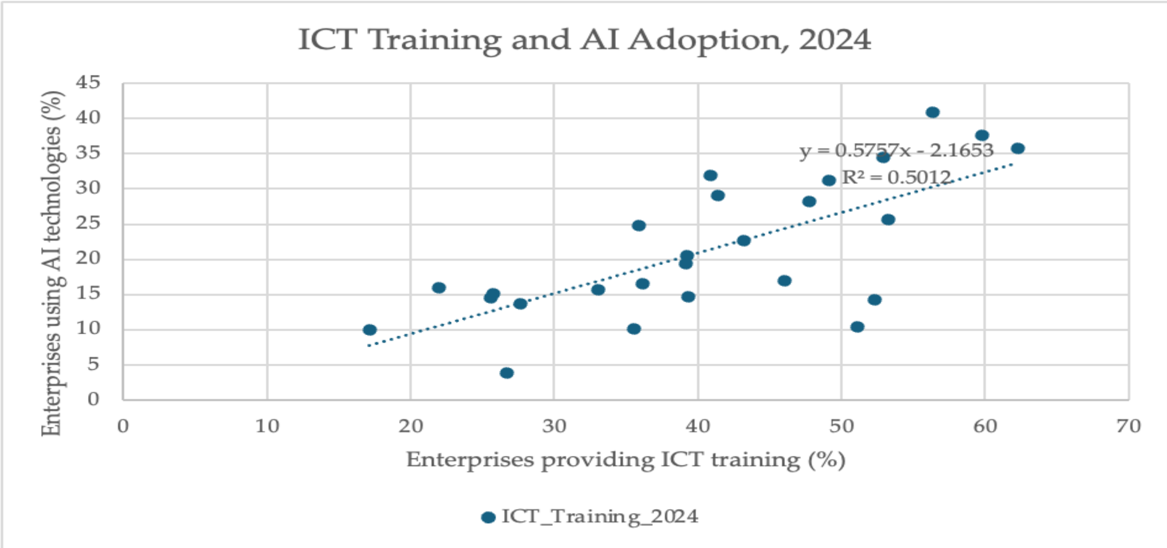

Figure 1. The association ICT training - AI adoption (N=26).

Note: Each point represents a state of the EU, and the dotted line shows the trend estimated by linear regression. Source: Authors' contribution based on Eurostat (2024).

Both graphs indicate positive relationships. However, the points are closer to the regression line in the case of ICT training, in accordance with the higher correlation value.

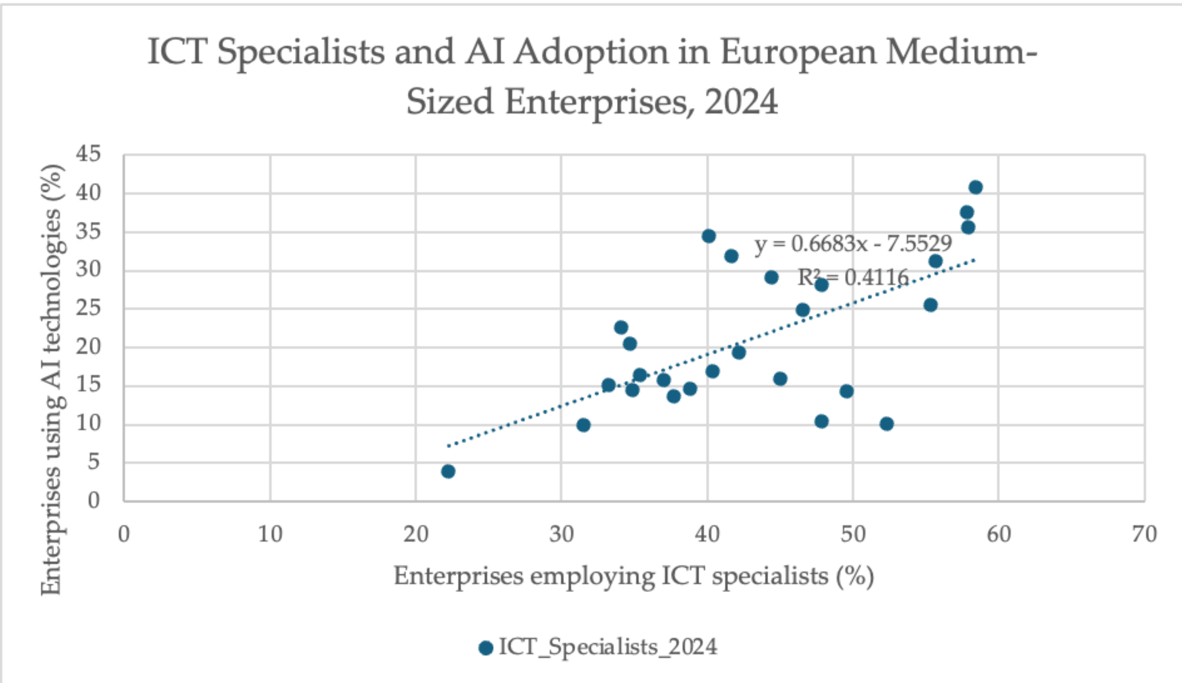

Figure 2. Association between employment of ICT specialists and adoption of AI (N=26).

Note: Each point represents a Member State; the dotted line indicates the linear regression. Source: Authors' contribution based on Eurostat (2024).

The model containing ICT training accounts for 50.1% of the cross-country variation in AI adoption, while the model containing ICT specialist use accounts for 41.2%. The two predictors are also strongly correlated ($r = 0.737$, $p < 0.001$), corresponding to approximately 54.2% shared variance. Therefore, they must be analysed together to see more clearly the role of each.

4.3 Regression models

All five regression models were statistically significant overall. However, not all individual predictors were statistically significant in the multiple regression models. Models based on ICT training and the employment of ICT specialists explain between 41.2% and 53.3% of the observed differences between states. In contrast, the recruitment difficulties model explains 27.8% of the variation, and the exploratory model, which includes all predictors, reaches 54.9%.

Table 6. *Model fit statistics of regression models. Source: Authors' contribution.*

Model	N	R^2	Adjusted R^2	F	p
M1: ICT Training	26	0.501	0.480	24.12	< 0.001
M2: ICT Specialists	26	0.412	0.387	16.79	< 0.001
M3: Training + Specialists	26	0.533	0.492	13.11	< 0.001
M4: Recruitment difficulties	26	0.278	0.248	9.26	0.006
M5: All predictors	25	0.549	0.485	8.53	< 0.001

In simple models, both ICT training ($B=0.576$, $p < 0.001$) and employment of ICT specialists ($B=0.668$, $p < 0.001$) are positively associated with AI adoption. The models explain 50.1% and 41.2% of the variance, respectively.

In the main model M3, ICT training remains significant ($B=0.418$, $p=0.023$), while the coefficient of ICT specialists is no longer significant ($B=0.273$, $p=0.225$). The non-significant coefficient does not mean that ICT specialists are less important. It indicates that, after controlling for ICT training, the data do not provide sufficient evidence of an independent association between ICT specialist employment and AI adoption in this sample. Rather, their association with AI adoption aligns substantially with the more general digital capability captured by ICT training. The model explains 53.3% of the variation in AI adoption.

Table 7. *Coefficients of the main model (M3). Source: Authors' contribution.*

Predictor	B	SE	t	p	95% CI
Constant	−7.56	6.56	−1.15	0.260	[−21.12; 6.00]
ICT training	0.418	0.171	2.44	0.023	[0.064; 0.773]
ICT specialists	0.273	0.219	1.25	0.225	[−0.181; 0.728]

Introducing the two predictors into the same model reduces the coefficient of training by 27.3%, but it remains significant. The coefficient of specialists decreases by 59.1% and loses significance. In terms of incremental R^2, training adds 0.121 over the model with specialists, and specialists add 0.032 over the model with training. This comparison indicates that ICT training provides more explanatory information than ICT specialist use in the present sample. However, the result should be taken into consideration as a conditional association preferably than causal effect evidence.

The result should be interpreted together with the high association between the predictors. The model shows that training has a distinct more stable association, but does not identify the mechanism by which this occurs.

Recruitment difficulties are positively linked with AI adoption in M4 (B=0.948, p=0.006), explaining 27.8% of the variation.

Table 8. *Coefficients of the model on recruitment difficulties (M4). Source: Authors' contribution.*

Predictor	B	SE	t	p	95% CI
Constant	10.87	3.82	2.85	0.009	[2.99; 18.76]
Recruitment difficulties	0.948	0.311	3.04	0.006	[0.305; 1.590]

In the exploratory model M5, estimated for 25 countries, only ICT training remains significant (B=0.397, p=0.039). The coefficients of ICT specialists and recruitment difficulties are not significant.

Table 9. *Exploratory model coefficients (M5). Source: Authors' contribution.*

Predictor	B	SE	t	p	95% CI
Constant	−6.93	6.91	−1.00	0.327	[−21.30; 7.44]
ICT training	0.397	0.180	2.21	0.039	[0.023; 0.771]
ICT specialists	0.192	0.236	0.81	0.426	[−0.300; 0.682]
Recruitment difficulties	0.338	0.318	1.06	0.300	[−0.323; 0.999]

Although M5 produces a slightly higher R^2 than the main model (0.549 compared with 0.533), its adjusted R^2 is marginally lower (0.485 compared with 0.492 for M3). This indicates that recruitment difficulties add limited explanatory value after accounting for ICT training and ICT specialist use. Together with the smaller sample and the different mechanism underlying the recruitment indicator, this result supports treating M5 as exploratory.

4.4. Diagnostics and sensitivity analyses

Diagnostic tests showed no significant problems with the main linear model. The variance inflation factor value was 2.19, which shows that ICT training and ICT specialist use contain some common information, but not enough to indicate severe multicollinearity. The tolerance value was approximately 0.46. Scatterplots indicated roughly linear relationships between predictors and AI adoption. Also, the Ramsey RESET test did not indicate problems related to the shape of the model (F=0.149, p=0.703).

The residuals showed a slight negative asymmetry, influenced in particular by the values for Poland and Cyprus. However, neither Shapiro–Wilk (W=0.933, p=0.092) nor the Jarque–Bera test (JB=2.699, p=0.259) showed a notable variation from normality. Meanwhile, the Breusch–Pagan test (p=0.249) and White test (p=0.548) did not indicate the presence of significant heteroscedasticity. Graphs for residuals and influence are presented in Appendix A.

The externally studentized residual values showed that Poland (−2.78) and Cyprus (−2.19) have the largest negative deviations from the values estimated by the model, and Hungary approached the conventional threshold (−1.94). Hungary had the highest Cook's distance value (D=0.265), followed by Poland (D=0.149) and Sweden (D=0.146). The value for Hungary exceeded the indicative threshold of 4/n=0.154. Greece and Romania had leverage values above the indicative threshold of 2(k+1)/n=0.231. These countries were retained in the main analysis and checked separately through sensitivity analyses. The diagnostic values for each country are presented in Table A1.

Table 10. *Diagnostic and sensitivity analyses for the main model. Source: Authors' contribution.*

Specification	N	ICT training B (SE)	p	ICT specialists B (SE)	p	Adjusted R^2
Full sample	26	0.418 (0.171)	0.023	0.273 (0.219)	0.225	0.492
Excluding Poland	25	0.482 (0.152)	0.005	0.251 (0.193)	0.207	0.603
Excluding Cyprus	25	0.468 (0.160)	0.008	0.269 (0.203)	0.199	0.572
Excluding Poland and Cyprus	24	0.541 (0.133)	< 0.001	0.245 (0.167)	0.156	0.710
Excluding Hungary	25	0.300 (0.173)	0.097	0.444 (0.225)	0.061	0.540
Excluding Romania	25	0.445 (0.174)	0.018	0.175 (0.243)	0.479	0.437
Excluding Greece	25	0.453 (0.204)	0.037	0.239 (0.248)	0.345	0.486
Full sample with HC3 robust SE	26	0.418 (0.188)	0.036	0.273 (0.250)	0.286	0.492

Note: B values are not standardized coefficients, with standard errors indicated in parentheses. In the HC3 specification, the coefficients and adjusted R^2 are unchanged; heteroscedasticity-robust standard errors and corresponding p values are reported.

Removing Poland and Cyprus, either separately or together, did not change the main conclusion. ICT training remained positively and statistically significantly associated with AI adoption, while ICT specialist use remained insignificant. The results remained broadly the same even when Romania or Greece were excluded.

The clearest change occurred after removing Hungary. The coefficient for ICT training remained positive but was no longer statistically significant at the 5% level (B=0.300, p=0.097). At the same time, the coefficient for ICT specialist use increased and approached the statistical significance threshold, but did not reach it (B=0.444, p=0.061). This result shows that Hungary influences to some extent the estimated relation between the two predictors.

The results were also checked using HC3 heteroscedasticity-robust standard errors. ICT training remained statistically significant (B=0.418, robust SE =0.188, p=0.036), while ICT specialist use remained insignificant (B=0.273, robust SE =0.250, p=0.286). The higher values of adjusted R^2 obtained after removing Poland and Cyprus do not mean that the reduced models are better. They only show that these two countries explain part of the variation that the full model does not capture. For this reason, the model estimated on the full sample remains the main basis for interpretation, even if the sensitivity towards Hungary should be mentioned.

4.5 National digital profiles

The classification by the two medians produces four profiles. The average adoption of AI is highest in the "consolidated digital ecosystem" profile (28.12%) and lowest in the "limited digital capability" profile (13.85%). The profile based more on internal training has an average of 26.49%, compared to 17.54% for the profile dependent on specialized expertise. The profiles are intended as a descriptive typology rather than statistically validated clusters. Differences in average AI adoption between the four groups are therefore presented for comparison and are not interpreted as statistically significant group effects.

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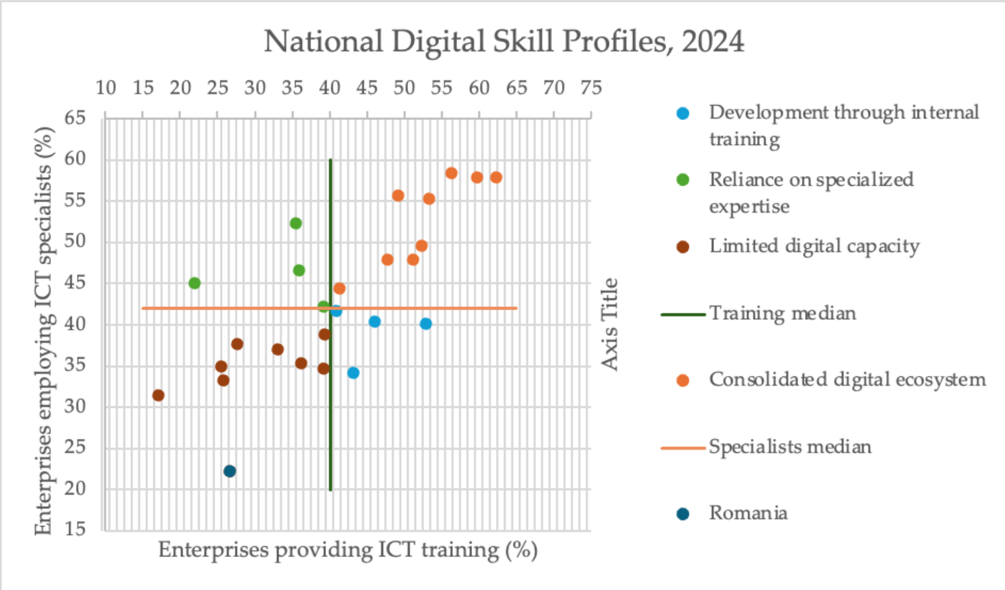

Figure 3. The national digital capability profiles.

Note: The vertical line draws the median of ICT training (40.14%), while the horizontal line indicates the median of ICT specialists employed (41.94%). Source: own contribution based on Eurostat data (2024).

***Table 11**. The national digital profiles and average adoption of AI. Source: Authors' contribution.*

Profile	No. of states	ICT training	ICT specialists	AI adoption
Consolidated digital ecosystem	9	52.60	52.75	28.12
Development through internal training	4	45.78	39.08	26.49
Reliance on specialized expertise	4	33.16	46.54	17.54
Limited digital capability	9	30.08	33.93	13.85

Figure 4 compares the average adoption of AI across the four profiles and illustrates the difference between states with more consolidated digital capability and those with more limited digital resources.

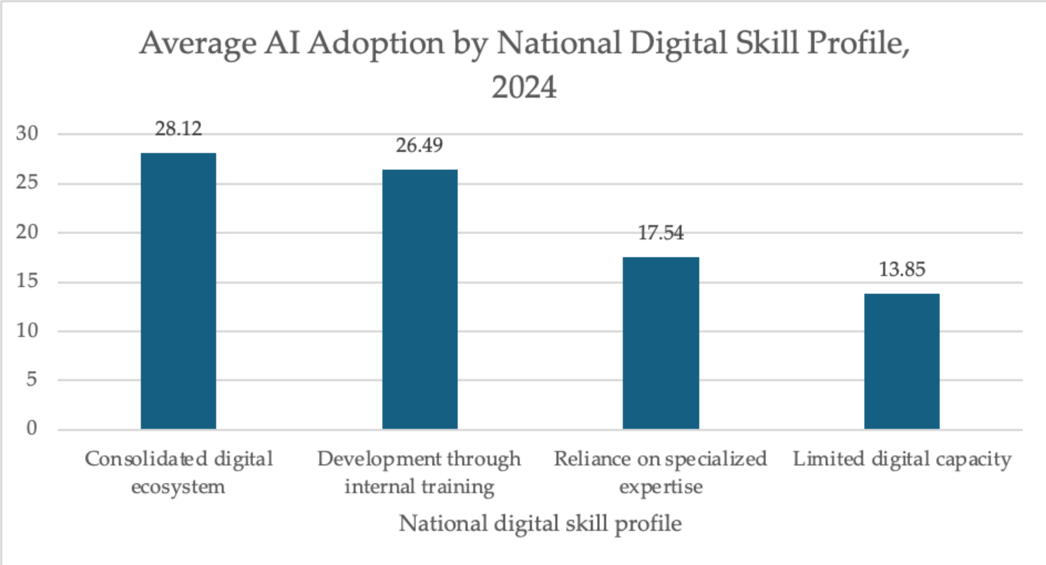

Figure 4. Average AI adoption by national digital capability profile, 2024. Source: Authors' contribution.

When states are grouped by level of ICT training, those in the high value category have an average AI adoption rate of 27.62%, compared to 14.99% in the low value group. The difference is smaller in the case of the employment of ICT specialists, where the averages are 24.86% and 17.74%, respectively. This classification has a descriptive role and does not represent a statistical test of differences between groups.

4.6 Romania's position within the EU

Romania belongs to the limited digital capability profile. In 2024, the values were 26.68% for ICT training, 22.24% for employment of ICT specialists, and 3.88% for adoption of AI. Among the 26 countries analysed, Romania ranks last in the adoption of AI and ICT specialists and 22nd in training.

AI adoption in Romania represents 18.2% of the sample average and is 17.42 percentage points lower. The biggest deficit occurs among ICT specialists: Romania is the only country below 30% and is 9.25 points below Bulgaria, the next country in the ranking.

The M3 model estimates an AI adoption of 9.68% for Romania, compared to the observed value of 3.88%. The difference of 5.80 percentage points corresponds to a standardized residual of −0.87, so Romania is not a statistical outlier. However, Romania has relatively high leverage because it combines low values for both ICT training and ICT specialist use. This means that its position in the predictor space is relatively unusual, even though its observed AI adoption is not an extreme deviation from the fitted model. Its position is mainly associated with the low level of digital capability.

Excluding Romania from the main model did not materially alter the result. ICT training remained positively and statistically significantly linked with AI adoption (B=0.445, p=0.018), whereas ICT specialist use remained non-significant (B=0.175, p=0.479). The main finding is therefore not driven by Romania's relatively unusual position in the predictor space.

In Romania, the percentage of enterprises that provided ICT training increased from 13.86% in 2022 to 26.68% in 2024. The increase was 12.82 percentage points. This comparison is only descriptive and should be interpreted with caution. The analysis carried out for a single year cannot demonstrate that this increase in training led to a greater adoption of artificial intelligence. The comparison depends on maintaining the same indicator definitions and the same sectoral coverage.

5. DISCUSSION

The results provide different answers to the three research questions. Analysed separately, both ICT training and the employment of ICT specialists are positively associated with AI adoption. When they are included in the same model, however, only training remains significant. This result suggests that ICT specialists have an important role to play, but their effect is closely connected to the wider level of digital skills in organizations. This result is consistent with the AMO model. Training can help technology to be used not only in technical departments, but also in other activities and processes of the organization (Bos-Nehles et al., 2023; Kettinger et al., 2015; Knies & Leisink, 2014).

The statistical analysis does not test this mechanism directly. The Eurostat indicator records whether an enterprise provided ICT training, but does not show how many employees participated, what skills were covered, how intensive the training was or whether the acquired skills were subsequently applied. The AMO-based explanation should therefore be understood as a theoretically informed interpretation of the observed association.

For medium-sized enterprises, the results suggest that recruiting a small number of specialists is not sufficient when the other organization lacks the skills needed for understanding and using the technology. The results should not be interpreted as evidence that specialist expertise can be replaced by general employee training. The two resources perform different functions: specialists support the technical development, implementation and maintenance of AI systems, while broader training helps managers and employees understand, evaluate and use these systems in practice. A combined approach is therefore more appropriate than choosing one of the two resources exclusively.

The positive association between recruitment difficulties and AI adoption does not mean that a shortage of specialist's favours adoption. A more conservative explanation is that more digitized economies have a higher need for ICT skills and therefore report more hard to-fill jobs (Bukartaite & Hooper, 2023).

This interpretation is not directly tested. The model demonstrates less than a third of this variation, and the indicator depends on the existence of vacancies and has a different reference population. The result should be treated as exploratory.

The low contribution of recruitment difficulties in the M5 model shows that the result should be interpreted with caution. After including ICT training and the employment of ICT specialists, recruitment difficulties no longer have a statistically significant effect, and the adjusted R^2 value does not increase. Therefore, the initially observed positive connection appears to indicate a greater demand for employees with digital skills rather than a factor independently influencing AI adoption.

Poland and Cyprus show why skills are not enough. Although they have above-average values for training and specialists, AI adoption remains below average. Factors not included in the models — for example, managerial priorities, sectoral structure, access to data, costs, or trust — may explain part of these deviations. The study cannot distinguish between these explanations.

These differences show that digital resources and skills alone are not enough to drive AI adoption. A company may have trained employees and ICT specialists, but may still face challenges such as lack of investment, limited access to data, insufficient management support, regulations, or lack of trust in the technology. These issues cannot be analysed with the data used in this study and should be investigated in the future.

In the case of Hungary, the results were more sensitive. After removing Hungary from the analysis, the relation between ICT training and AI adoption remained positive but was no longer statistically significant at the 0.05 level. At the same time, the coefficient for the employment of ICT specialists increased and approached the statistical significance threshold. This result does not change the conclusion of the estimated model for the entire sample, but shows that the difference between the two components of digital capability is influenced to some extent by high-influence observations.

The Romanian case indicates a simultaneous deficit in training, expertise and use of AI. The observed value is below that estimated by the model, but not enough to be considered atypical. The increase in training between 2022 and 2024 is encouraging, but its effect cannot be evaluated without longitudinal data and firm-level information.

The study has several limitations. First, the cross-sectional design does not determinate the temporal order or causal relationships. Second, country-level data may conceal substantial differences between enterprises, sectors and regions and do not allow firm-level conclusions. Third, the small number of EU States limits the complexity of regression models and the precision of coefficient estimates. Models were therefore intentionally kept parsimonious. Fourth, the analysis does not include potentially relevant factors such as investment levels, management quality, data availability, digital infrastructure, regulation, sectoral composition or organizational culture. Fifth, the median-based profiles are descriptive and should not be interpreted as statistically validated clusters. Finally, possible regional dependence between EU Member States is not explicitly modelled.

Future research could combine longitudinal country-level indicators with firm-level data and more detailed measures of ICT training, including participation rates, duration, content and subsequent use of the acquired skills. Additional studies could also examine whether the relation between digital capability and AI adoption varies by sector, institutional context or level of economic development.

6. CONCLUSION

This study investigated the relation between two components of the digital capability — ICT training of employees and the employment of ICT specialists — and the adoption of artificial intelligence in medium-sized enterprises in the European Union. The results show that both components are positively associated with AI adoption when analysed separately. However, when introduced into the same model, only ICT training retains a significant association. This result suggests that specialized expertise is important, but AI integration seems to depend more strongly on the spread of digital skills throughout the organization.

The central contribution of the study consists in separating two dimensions that are often treated together. ICT specialists provide the technical knowledge needed to select, implement and maintain digital solutions, while training helps managers and employees understand these solutions and use them in their daily work. For medium-sized enterprises, the results thus support a combined approach, in which technical expertise is complemented by the development of skills across the organization.

The analysis also highlights large differences between European Union countries. Countries with higher levels of the ICT training also seem to have higher rates for AI adoption, although the cases of Poland and Cyprus show that digital resources alone do not explain all the differences. In the case of Romania, low levels of training, employment of ICT specialists and adoption of AI overlap, and the rate of 3.88% places the country in the last position in the sample. This situation may be related to limited digital capability, but also to other factors that were not included in the analysis, such as investment, managerial priorities, the structure of economic sectors or trust in new technologies.

The positive association between recruitment difficulties and AI adoption should be interpreted with caution. It does not show that the lack of specialists encourages the use of AI but may reflect the fact that more digitalized economies have a greater need for ICT skills and more often encounter problems in filling these positions. For this reason, the role of this indicator remains exploratory.

The conclusions of the study should be seen within the limits of the data used. The analysis is based on aggregated information for a single year and can identify associations across countries but cannot demonstrate causal relationships or describe the behaviour of individual firms. Future research could combine data analysed over time with information at the firm level and with more detailed indicators on training participation, program content, and how acquired skills are used in practice. This method would enable for a clearer understanding of how digital capability translates into effective and responsible use of artificial intelligence.

7. APPENDIX A: REGRESSION DIAGNOSTIC PLOTS

Table A1. *Diagnostic tests for model M3. Source: Authors' contribution.*

Test	Statistic	Value	p
Ramsey RESET	F	0.149	0.703
Shapiro–Wilk	W	0.933	0.092
Jarque–Bera	JB	2.699	0.259
Breusch–Pagan	LM	2.783	0.249
White test	LM	4.012	0.548

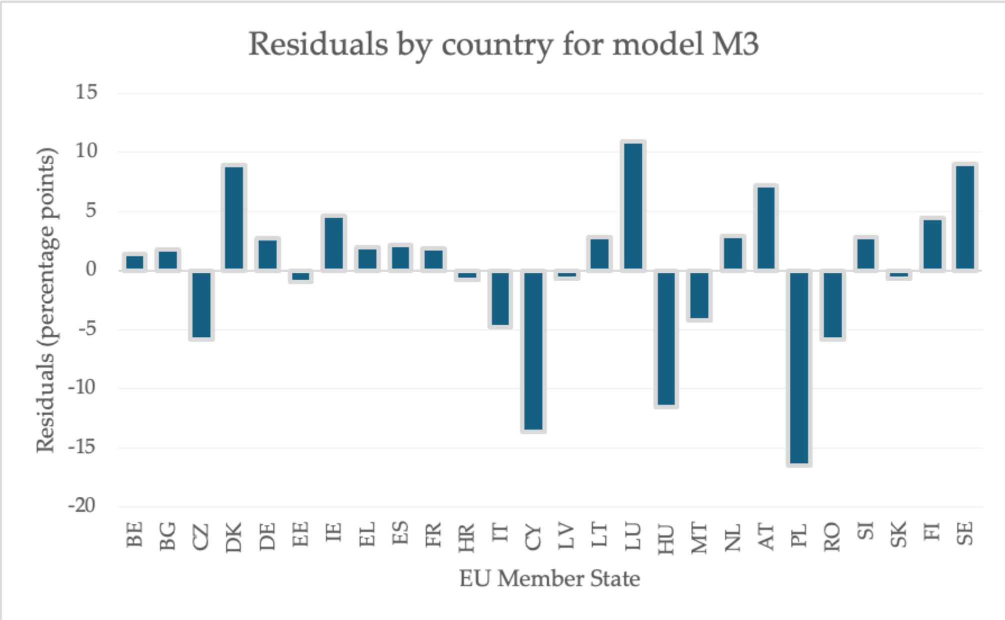

Figure A1. Residuals by country for model M3;

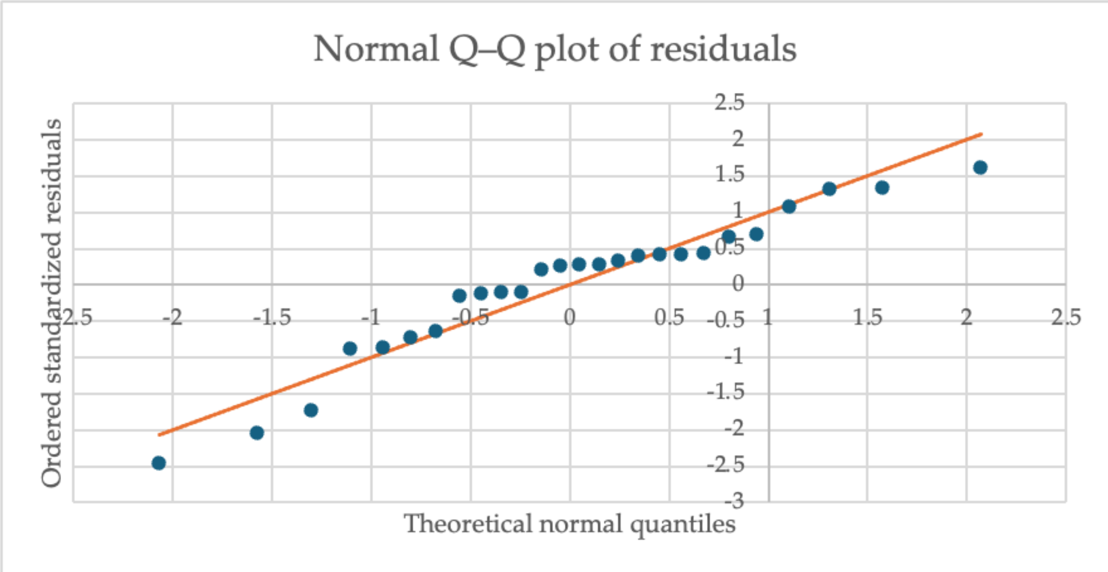

Figure A2. Normal Q–Q plot of residuals for model M3;

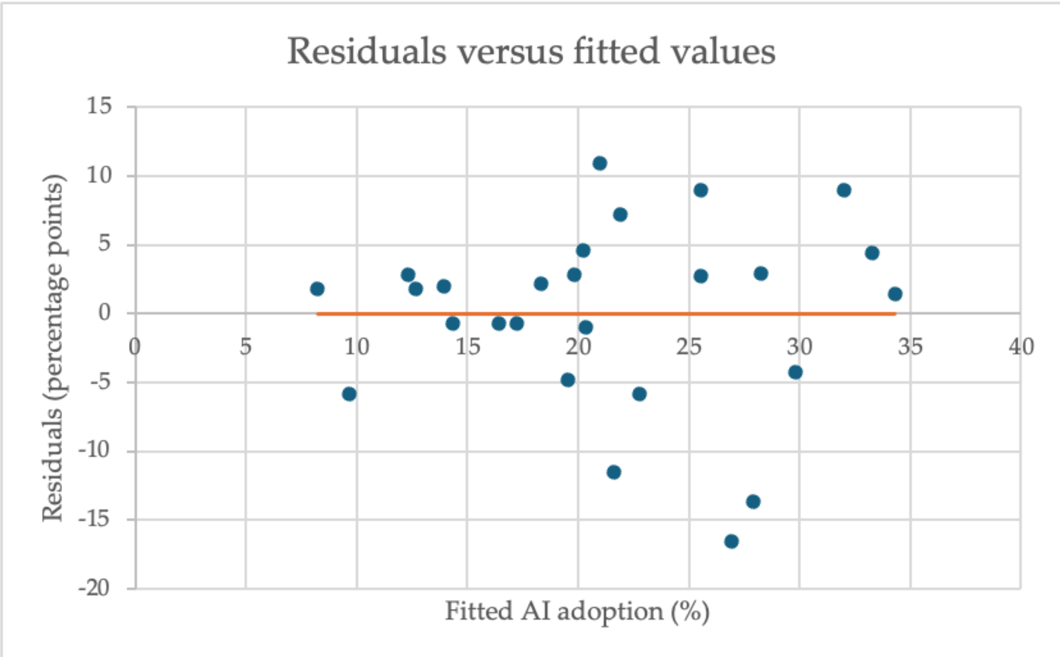

Figure A3. Residuals versus fitted value for model M3;

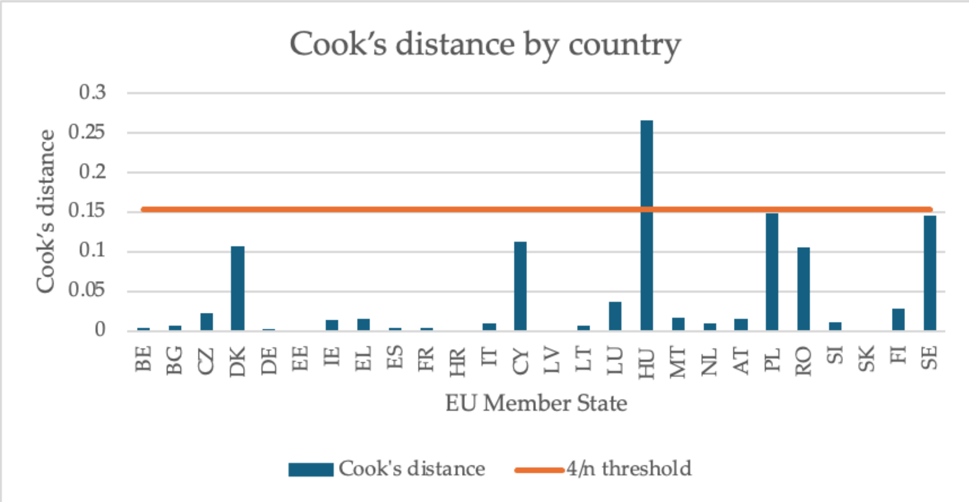

Figure A4. Cook's distance by country for model M3;

Table A2. *Country-level influence diagnostics for model M3. Source: Authors' contribution based on Eurostat data (2024).*

Country	Leverage	Externally studentized residual	Cook's distance	DFFITS
Belgium	0.171	0.215	0.003	0.098
Bulgaria	0.195	0.276	0.006	0.136
Czechia	0.080	-0.868	0.022	-0.256
Denmark	0.144	1.411	0.107	0.579
Germany	0.052	0.390	0.003	0.092
Estonia	0.039	-0.146	0.000	-0.030
Ireland	0.083	0.684	0.014	0.205
Greece	0.294	0.326	0.015	0.210
Spain	0.097	0.324	0.004	0.106
France	0.102	0.273	0.003	0.092
Croatia	0.071	-0.110	0.000	-0.030
Italy	0.052	-0.698	0.009	-0.163
Cyprus	0.076	-2.188	0.112	-0.625
Latvia	0.090	-0.100	0.000	-0.031
Lithuania	0.102	0.415	0.007	0.140
Luxembourg	0.041	1.652	0.036	0.342
Hungary	0.191	-1.942	0.265	-0.944
Malta	0.105	-0.636	0.016	-0.218
Netherlands	0.116	0.443	0.009	0.161
Austria	0.039	1.055	0.015	0.213
Poland	0.070	-2.782	0.149	-0.760
Romania	0.256	-0.960	0.106	-0.563
Slovenia	0.147	0.430	0.011	0.179
Slovakia	0.058	-0.097	0.000	-0.024
Finland	0.152	0.676	0.028	0.286
Sweden	0.179	1.451	0.146	0.678

CONFLICTS OF INTEREST AND PLAGIARISM: The authors declare no conflict of interest and plagiarism.

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