Discussion Papers

Explaining AI Adoption Across the Euro Area: Labour Market Incentives, Digital Capabilities and Sectoral AI Exposure

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Table of contents

Abstract 4

1 Introduction 5

2 Developments in Digital Investment 6

3 AI-related Data and Stylised Facts 8
- 3.1 AI adoption data 8
- 3.2 AI exposure 10
- 3.3 Other explanatory variables and sample construction 11
- Labour costs, labour productivity and labour market conditions 12
- Digital skills, education and infrastructure 13
- Costs and market concentration 13

4 Empirical Methodology 14
- 4.1 Baseline specification 14
- 4.2 Alternative specification: A two-way fixed effects model 15

5 Results 15
- 5.1 Labour costs and AI adoption 15
- 5.2 Other possible determinants of AI adoption 17
- Labour market conditions 17
- Digital skills, education and infrastructure 17
- Costs and market concentration 19
- 5.3 Consolidated results and synthesis 20
- 5.4 Labour costs and AI exposure 22
- 5.5 Robustness and reverse causality identification 24
- Dynamic panel specification 24
- Reverse causality diagnostics 25

6 Policy Implications and Conclusion 27

7 References 28

Abstract[1]

This paper examines the determinants of artificial intelligence (AI) adoption across euro area countries and industries. We combine Eurostat data on AI adoption with country–industry indicators of labour costs, labour market conditions, digitalisation, skills, and energy and financing costs over 2021–2025. We also construct a sectoral measure of AI exposure by combining occupation-level generative AI exposure scores with the occupational composition of employment across industries. Using panel regressions with country, industry and year fixed effects (FE), we find robust evidence of labour-cost-driven AI adoption, with higher labour compensation linked to stronger AI adoption across specifications. This labour cost channel is considerably stronger in industries with greater technological exposure to AI, suggesting that higher labour costs create stronger incentives for adoption where there is greater scope for AI-based automation or augmentation. Digital intensity and information and communication technology (ICT) training also emerge as important determinants of AI adoption. By contrast, we find no robust evidence that labour productivity, labour market tightness, education, energy costs, financing costs and market concentration independently explain AI adoption. Overall, the results suggest that AI adoption depends on both economic incentives and firms' technological and organisational capacity to implement AI.

JEL classification: O33, J31, J24, C23

Keywords: artificial intelligence, AI adoption, labour costs, automation, digitalisation, AI exposure, euro area

[1] The authors would like to thank Robert Zorko (Banka Slovenije) for his in-depth review of the paper.

1 Introduction

Following the release of Chat GPT and the widespread availability of generative artificial intelligence (AI) tools, their adoption and use by firms have increased markedly since 2022. As highlighted in analysis by Bick et al. (2025, 2026a, 2026b, 2026c), Misch et al. (2025) and OECD/BCG/INSEAD (2025), AI adoption data point to substantial heterogeneity across firms and sectors worldwide. The variation in AI adoption is considerable even within the euro area, despite a relatively comparable policy and institutional setting. This is further supported by findings from the firm-level analysis using survey data (Ferrando et al., 2026).

In the context of AI adoption, Acemoglu (2024) emphasises the core economic mechanism: even if tasks are technically automatable, adoption occurs only when expected benefits exceed costs. In practice, this means that firms will invest and adopt AI technologies only when they become profitable, taking into account implementation cost, organisational adjustment, complementary investments, and current uncertainties regarding the future benefits and regulatory framework of AI. This suggests that even when AI technologies are available, their adoption tends to be uneven across firms due to differences in cost structures, existing digital infrastructure, access to (AI) skilled labour, managerial practices with limited clarity on the potential benefits of AI technologies, etc.

According to responses to the ECB's Survey on the Access to Finance of Enterprises (SAFE), firms identify expected improvements in business processes and reduction of personnel costs as relevant drivers of AI adoption, while the main obstacles include AI skill shortages and system incompatibilities (Ferrando et al., 2026). The role of labour costs in AI adoption is also highlighted in the empirical analysis by Misch et al. (2025), while other studies emphasise the importance of proactive management practices and stronger organisational support (Bick et al., 2026b; Ropele and Tagliabracci, 2026).

Leveraging on Misch et al. (2025), this analysis investigates the determinants of AI adoption across euro area countries and industries. The analysis combines Eurostat indicators on enterprise AI adoption with sectoral indicators covering labour costs, broader labour market characteristics, digitalisation, ICT skills and energy costs. Data on financing costs are obtained from AnaCredit, while AI exposure is constructed using the occupation-level generative AI exposure scores developed by Gmyrek et al. (2025). The empirical strategy relies primarily on fixed-effects panel regressions at the country–industry–year level.

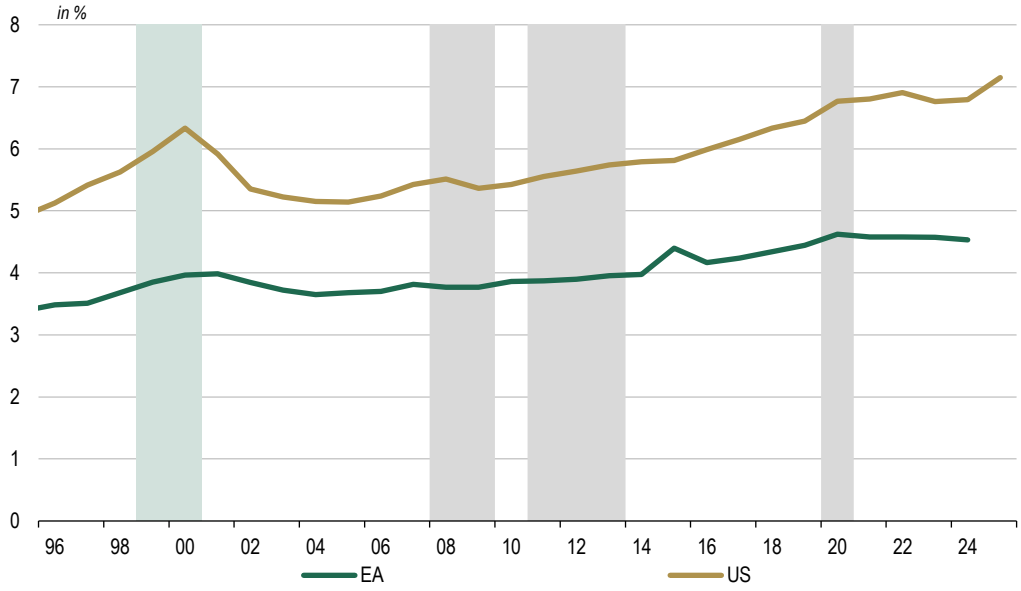
The results show that labour compensation is consistently and positively associated with AI adoption, suggesting that labour costs are an important determinant of firms' AI adoption decisions. Higher labour costs appear to strengthen incentives for task automation and adoption of AI technologies, particularly in industries which are more exposed to AI technologies. In addition, digital intensity and ICT training are likewise strongly associated with AI uptake, suggesting that firms require complementary investments in digital infrastructure and skills to successfully integrate AI technologies into business processes. By contrast, labour productivity, labour market tightness, education level, energy costs, cost of financing and market concentration show limited explanatory power once country, industry and year effects are taken into account.

The remainder of the paper is organised as follows. Section 2 provides an overview of developments in digital investment. Section 3 describes the data and sample construction. Section 4 outlines the empirical strategy. Section 5 presents the results and Section 6 concludes with policy implications.

2 Developments in Digital Investment

Recent advances in AI have increased the relevance of digital investment as a prerequisite for the development, deployment and use of these technologies. Since the broad diffusion of generative AI tools in late 2022, firms have faced stronger incentives to invest in complementary digital capital, including ICT equipment, software and databases, and research and development (R&D). While these categories do not provide a direct measure of AI investment, they capture capital expenditure closely linked to the digital infrastructure, software assets and innovation capacity needed to develop and adopt AI technologies.

Figure 1: **Share of digital investments**



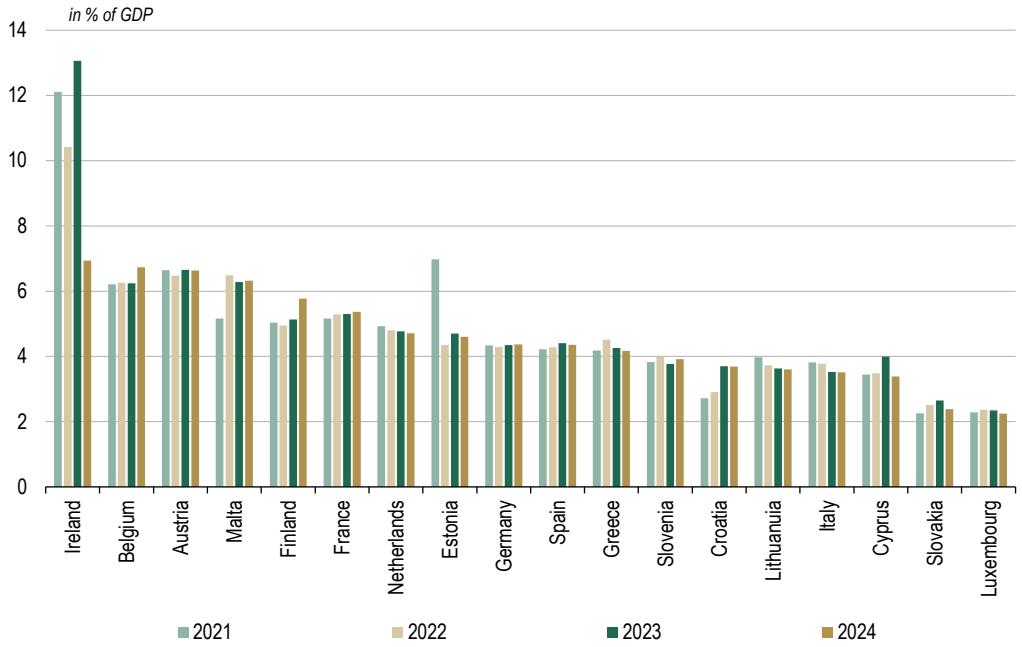
Sources: Eurostat, FRED, Bank Slovenije calculations.
Note: The share of digital investment is defined as the ratio between total investment in information and communication technology equipment, software and databases, and R&D, and GDP, expressed in current prices. The grey shaded areas indicate periods of economic crises in the euro area, while the green shaded area marks the dot-com cycle. The aggregated share of digital investment for the euro area is calculated excluding Ireland, due to the pronounced volatility of the data.

Digital investment, measured as a share of GDP, followed a broadly similar trajectory in the euro area and the United States during the dot-com period, with both economies recording a marked increase followed by a correction after the dot-com bust (Figure 1). Since then, however, the expansion has been considerably stronger in the United States, particularly after 2014. As a result, the United States entered the recent AI cycle with a larger digital capital base. In 2024, digital investment accounted for 4.5% of GDP in the euro area, compared with 6.8% in the United States. In 2025, digital investment

in the United States increased further, reaching 7.2% of GDP, while euro area data for this year are not yet available.

Digital investment also varies considerably across euro area countries. In 2024, digital investment accounted for around 2.2% of GDP in Luxembourg and 2.4% in Slovakia, compared with around 6.6–6.9% in Austria, Belgium and Ireland, with the last experiencing pronounced volatility (Figure 2). These differences point to substantial heterogeneity in digital capital accumulation across the euro area, which may in turn shape countries' capacity to develop and adopt AI technologies.

Figure 2: **Share of digital investments across euro area countries**



Sources: Eurostat, FRED, Bank Slovenije calculations.
Note: The share of digital investment is defined as the ratio between total investment in information and communication technology equipment, software and databases, and R&D, and GDP, expressed in current prices.

However, digital investment share should not be interpreted as a direct measure of a country's capacity to adopt AI. While investment in digital technologies provides an important enabling condition, it does not necessarily translate into actual use of AI technologies. Looking beyond digital investment, AI adoption also depends on firms' digital readiness, skills and organisational capacity to integrate these technologies effectively into their production processes (OECD/BCG/INSEAD, 2025; Ferrando et al., 2026). The remainder of the paper therefore empirically assesses the determinants of AI adoption across euro area countries and industries.

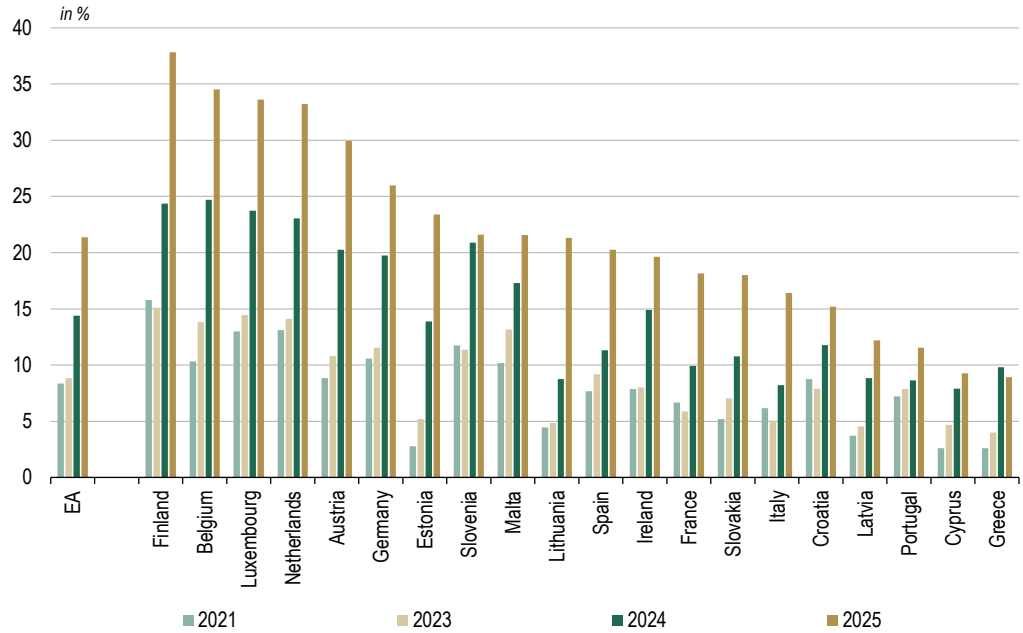
3 AI-Related Data and Stylised Facts

This section describes the data used in the analysis and the construction of the main variables and their characteristics in the sample.

3.1 AI adoption data

For the purpose of this analysis, we use data on AI adoption rate across euro area countries and sectors (1-digit NACE), measured as the share of firms using at least one of the AI technologies.[2] Data has been collected annually since 2021 by Eurostat and National Statistical Institutes as part of the survey on ICT Usage and E-Commerce in Enterprises, with the exception of 2022, when the AI module of the survey was not included. As specified in the survey details, AI refers to systems that use technologies such as text mining, computer vision, speech recognition, natural language generation and speech synthesis, and machine learning or deep learning. These technologies enable systems to analyse data and generate predictions, recommendations or decisions with varying degrees of autonomy. AI applications may be software-based, such as virtual assistants and image-recognition systems, or embedded in physical devices, including autonomous robots, drones and self-driving vehicles (Eurostat, 2026).

Figure 3: **AI adoption rate across euro area countries**



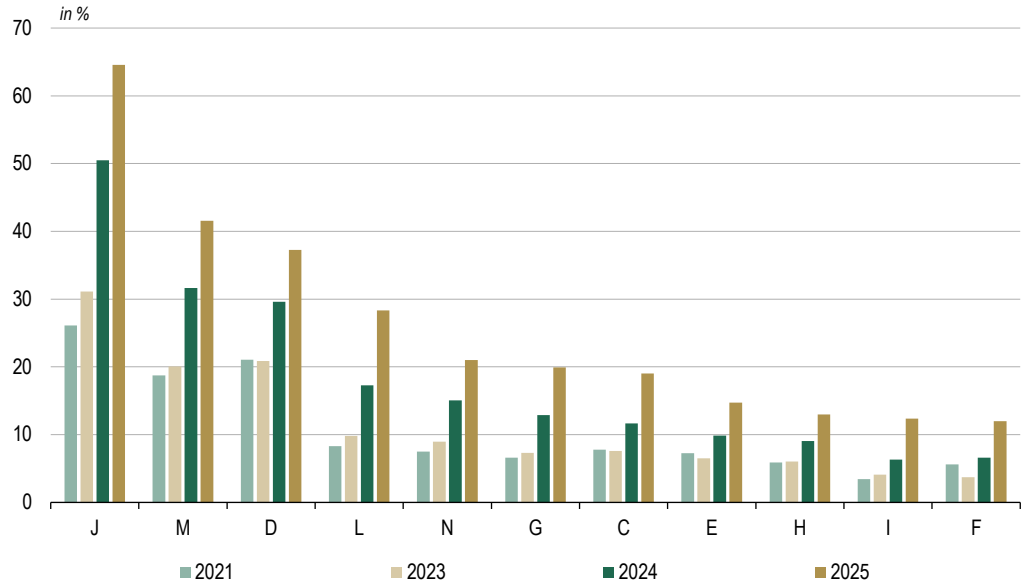
Source: Eurostat.
Note: The figure presents AI adoption rates across euro area countries, defined as the share of firms using at least one AI technology. The data includes all economic activities except agriculture, forestry and fishing, mining and quarrying, and the financial sector.

Survey data indicate that the use of AI technologies by euro area enterprises has increased markedly in recent years. Up to 2023, the adoption of AI technologies among euro area firms remained relatively limited. Only 9% of firms reported using at least one AI technology, representing an increase of just 1 percentage point (pp) compared with 2021. A substantial and broad-based acceleration in AI adoption was recorded in 2024 and 2025, with the share of euro area firms using AI increasing to 14% and 21% respectively. Despite the overall upward trend, adoption rates differ markedly across

[2] The main findings are robust to alternative measures of AI adoption, defined as the share of firms using at least two or at least three AI technologies instead of at least one AI technology.

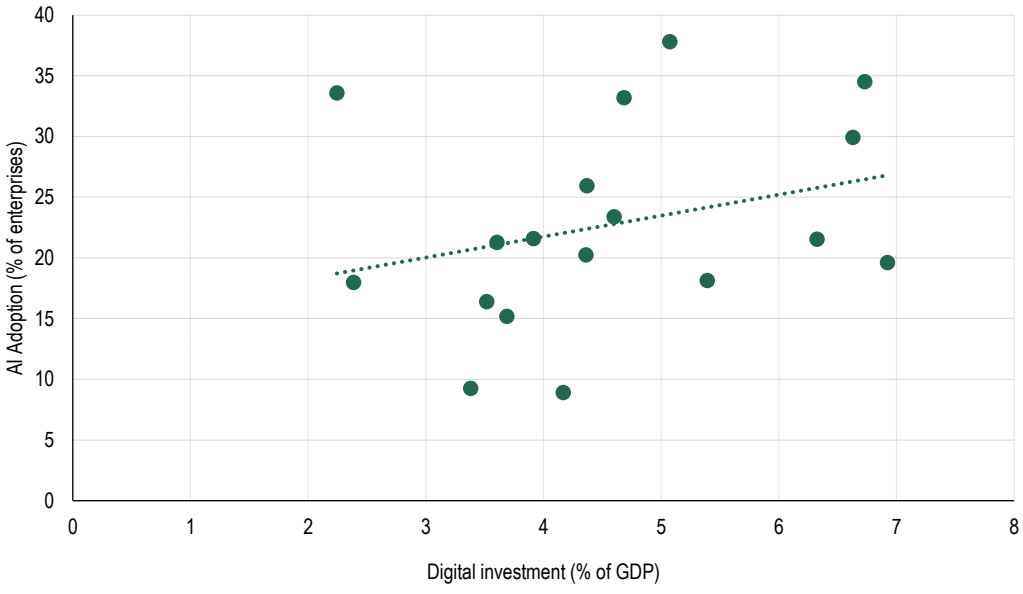
countries and industries. In 2025, AI adoption in euro area countries ranged from 9% in Greece to 37% in Finland (Figure 3). Across economic activities, the lowest AI adoption is recorded in construction, at 12%, in contrast to the AI adoption rate of 65% in information and communication sector (Figure 4).

Figure 4: **AI adoption rate across industries**



Source: Eurostat.
Note: The figure presents AI adoption rates across industries, defined as the share of firms using at least one AI technology. The data includes all economic activities except agriculture, forestry and fishing, mining and quarrying, and the financial sector, i.e. information and communication (J); professional, scientific and technical activities (M); electricity, gas, steam and air conditioning supply (D); real estate activities (L); administrative and support service activities (N); wholesale and retail trade; repair of motor vehicles and motorcycles (G); manufacturing (C); water supply; sewerage, waste management and remediation activities (E); transportation and storage (H); accommodation and food service activities (I); construction (F).

Figure 5: **AI adoption and digital investment across euro area countries**



Sources: Eurostat, Banka Slovenije calculations.
Note: The figure plots 2025 AI adoption rates across euro area countries against the 2024 share of digital investment in GDP.

At the country level, higher digital investment is associated with higher AI adoption, although the relationship is relatively modest (Figure 5). This pattern is consistent with digital investment acting as an enabling factor for AI adoption by strengthening firms'

digital infrastructure, software base and innovation capacity. However, the relationship should not be interpreted as causal. Moreover, the dispersion around the fitted line suggests that digital investment alone cannot explain cross-country differences in AI adoption. The analysis therefore considers additional determinants, including labour costs, digital skills, education level and other input costs.

3.2 AI exposure

To measure the technological applicability of AI across industries, we use the job-title-level generative AI exposure scores developed by Gmyrek et al. (2025). Their methodology evaluates each task on a scale from 0 to 1 according to its exposure to generative AI, with higher values indicating greater potential for AI-driven automation or transformation.

We construct an AI exposure index at the country–industry–year level in three steps. First, we average the job-title-level exposure scores of Gmyrek et al. (2025) within each ISCO-08 one-digit occupation group. Second, we use Eurostat Labour Force Survey data on employment of persons aged 20–64 to compute each occupation's share in employment by country, industry and year. Finally, we define AI exposure as a weighted average of occupational AI exposure scores, with weights equal to occupations' employment shares:

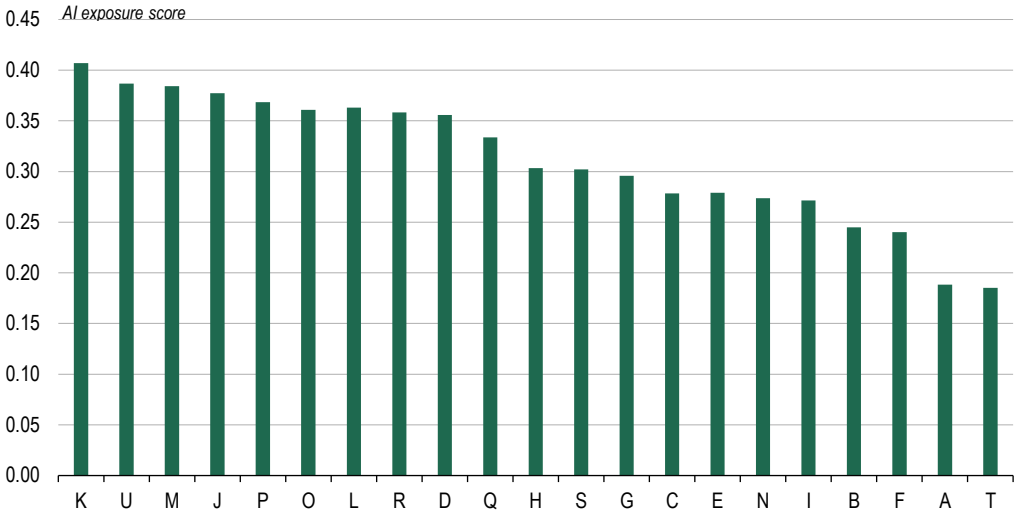
$$AI_Exposure_{ijt} = \sum_o \frac{L_{oijt}}{L_{ijt}} E_o,$$

where o, i, j and t index occupations, industries, countries and years respectively. E_o denotes the mean Gmyrek et al. (2025) exposure score of the job titles in occupation o, L_{oijt} is the employment in occupation o in country i, industry j and year t, and L_{ijt} is total employment in that country–industry–year cell. Employment shares are computed over occupations for which an exposure score is available.

The resulting AI exposure index captures the technological potential for AI to affect tasks performed within an industry rather than observed AI adoption. Higher values indicate that a larger share of employment is concentrated in occupations whose tasks are more exposed to AI.

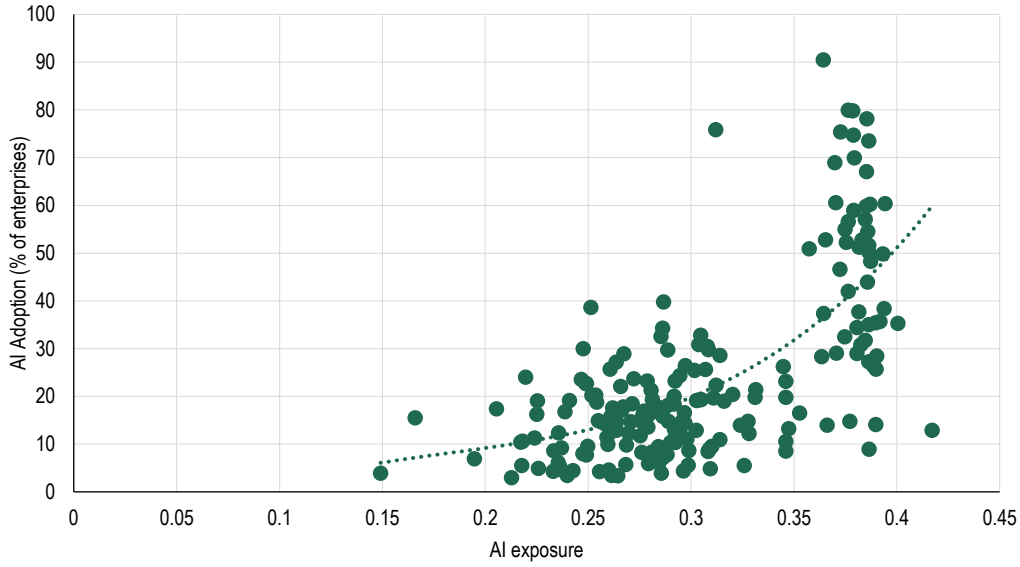
AI exposure varies considerably across euro area industries. In 2025, it was highest in financial and insurance activities, at around 0.41, followed by professional, scientific and technical activities, information and communication activities, and activities of extraterritorial organisations, at around 0.38–0.39. By contrast, exposure was lowest in agriculture and household activities, at around 0.19 (Figure 6). Across euro area country–industry observations, higher AI exposure is associated with higher observed AI adoption, as indicated by the upward-sloping fitted line in Figure 7. However, the wide dispersion of observations suggests that exposure alone does not account for differences in adoption, and the relationship should be interpreted as descriptive rather than causal.

Figure 6: **AI exposure across industries**



Sources: Eurostat, Gmyrek et al. (2025), Banka Slovenije calculations.
Note: The figure presents employment-weighted generative AI task exposure across euro area industries in 2025. Industry-level exposure is constructed by combining occupation-specific GenAI exposure scores from Gmyrek et al. (2025) with Eurostat data on the occupational composition of employment within each industry. The figure covers agriculture, forestry and fishing (A); mining and quarrying (B); manufacturing (C); electricity, gas, steam and air conditioning supply (D); water supply, sewerage, waste management and remediation activities (E); construction (F); wholesale and retail trade and repair of motor vehicles and motorcycles (G); transportation and storage (H); accommodation and food service activities (I); information and communication (J); financial and insurance activities (K); real estate activities (L); professional, scientific and technical activities (M); administrative and support service activities (N); public administration and defence and compulsory social security (O); education (P); human health and social work activities (Q); arts, entertainment and recreation (R); other service activities (S); activities of households as employers and undifferentiated goods- and services-producing activities of households for own use (T); and activities of extraterritorial organisations and bodies (U).

Figure 7: **AI adoption and AI exposure across euro area industries in 2025**



Sources: Eurostat, Gmyrek et al. (2025), Banka Slovenije calculations.
Note: The figure plots 2025 AI adoption rates against 2025 AI exposure across euro area country–industry observations. AI adoption is measured as the percentage of enterprises using at least one AI technology, while AI exposure captures the average occupational task-exposure score within each industry, weighted by the industry's occupational employment structure.

3.3 Other explanatory variables and sample construction

Our data sample consists of observations at the country–sector–time level, covering 20 euro area countries and approximately 11 sectors over the period 2021–2025, excluding 2022. In the scope of this analysis, we examine several possible determinants of AI adoption, which may be grouped into the following categories: labour-market-related

indicators; digital skills, education and infrastructure; other input costs; and market concentration. All the explanatory variables are collected from Eurostat, but some are available only for shorter periods or at more aggregate levels. This subsection therefore provides a more detailed description of the possible determinants of AI adoption used as explanatory variables.

Labour costs, labour productivity and labour market conditions

Labour compensation

Compensation of employees per hour worked is used to capture labour costs borne by employers. According to Eurostat methodology, compensation of employees includes wages and salaries as well as employers' social contributions. The average value of labour compensation in our sample amounts to EUR 26.6 per hour, with standard deviation at EUR 14.4 per hour. The baseline concept we aim to analyse is whether firms with higher labour costs are more likely to adopt AI. In line with a cost–benefit economic mechanism, higher labour costs increase the potential savings from automation and therefore strengthen incentives to adopt AI technologies (Acemoglu, 2024). However, as high-wage work environments are also more educated and technologically advanced, other possible determinants of AI adoption, specified in the remainder of this section, are considered in the subsequent estimations.

Labour productivity

Labour productivity, measured as real output per hour worked, can be viewed as a proxy for technological advancement and efficiency. The inclusion of labour productivity may reduce omitted variable bias, as more productive firms tend to pay higher wages and may also be more likely to adopt AI technologies. In our data sample, the average value and standard deviation of the labour productivity index amount to 104 and 24.8 respectively.

Job vacancy rate

The analysis considers job vacancy rates as a potential driver of AI adoption, capturing labour shortages and recruitment difficulties faced by firms. In particular, when job vacancies are high, firms may struggle to hire and may have stronger incentives to automate or augment tasks. On the other hand, if vacancies reflect shortages in AI-complementary skills, then the increase in job vacancies would slow AI adoption. In our data sample, the average value and standard deviation of the job vacancy rate amount to 2.5% and 1.8 pp respectively.

Employed ICT specialists

To complement job vacancies data, we include in the analysis measures of ICT specialist recruitment and ICT employment shares. While high-tech sectors with high ICT hiring may have both higher wages and higher AI adoption, these variables may also proxy for firms' digital capabilities and organisational readiness. ICT specialist employment is defined as the share of employed ICT specialists in total employment, varying only at the country level. The average share of employed ICT specialists amounts to 5.0%, with a standard deviation of 1.3 pp. As an alternative measure, we use the share of enterprises that recruited or tried to recruit ICT specialists, which is available at the country–sector level but only for 2020, 2022 and 2024. In our sample, the average share of firms that recruited or tried to recruit ICT specialists amounts to 53.4%, with a standard deviation of 22 pp.

Digital skills, education and infrastructure

Digital intensity and digital infrastructure

The digital intensity index measures the share of firms meeting a set of digitalisation criteria, including internet connectivity, cloud services, ICT security practices, ICT specialists, ICT training to employees and use of AI-related technologies. In the estimation, we use the share of firms in each country–sector that are classified as having a high or very high digital level. In our sample, the share of high digitally intensive firms averages 33.8%, with a standard deviation of 22.8 pp. While sectors with higher digital intensity may be better positioned to adopt and integrate AI technologies by leveraging on existing skills and infrastructure, they may also exhibit higher wage levels due to their larger share of highly skilled workers. Therefore, including digital intensity in the estimation helps to identify in a cleaner way the labour cost channel associated with AI adoption. In line with the persistence of AI adoption, it is expected that the estimated coefficient on lagged digital intensity will be significant and positive, as the index also incorporates the use of AI technologies.

ICT training

For identification purposes and to complement the digital intensity index, we include in the analysis as a stand-alone explanatory variable the share of firms providing training to their personnel to develop their ICT skills. In our sample, the average share of firms that provided ICT training amounts to 26.5%, with a standard deviation of 18.5 pp. ICT training may proxy for management readiness to implement AI, since firms that invest in workers' digital skills are likely to have more proactive management practices, stronger organisational support and greater capacity to integrate new technologies into workflows (Bick et al., 2026b). As also highlighted by OECD/BCG/INSEAD (2025), managers often struggle to understand the practical applications of AI for their business needs and simultaneously underestimate the enterprise-wide implication and potential benefits of AI adoption. In addition, according to the Eurostat survey, the lack of relevant expertise was the most commonly cited reason for not using AI among firms that had considered its adoption, reported by more than 70% of respondents.

Education level

In addition, we consider the share of employed persons with tertiary education. Similarly to the case of digital skills and infrastructure, sectors with more skilled workers may have higher wages and at the same time also the capacity for faster AI adoption. Data on education collected from Eurostat varies across countries only. In our data sample, the share of employed persons with tertiary education has a mean of 42.0% and a standard deviation of 8.5 pp.

Costs and market concentration

Energy costs

To examine whether energy costs affect incentives for AI adoption, we use electricity prices for non-household consumers (annual consumption band of 2,000–19,999 MWh) as an indicator of the energy cost pressures faced by firms. Higher energy costs may encourage firms to adopt AI technologies to optimise operations, reduce waste and improve energy efficiency.[3] In our sample, electricity prices vary only at the country

[3] AI technologies can improve energy efficiency by analysing real-time operational data to identify inefficient production patterns and optimise equipment settings, production schedules and resource allocation. It can also adjust heating, cooling

level, with a mean of EUR 0.18 per kilowatt-hour and a standard deviation of EUR 0.062 per kilowatt-hour.

Cost of financing

The adoption of AI technologies may require sizable investment, leading firms to rely on external financing to support the implementation of AI. Consequently, access to external financing and financing conditions may influence firms' incentives to invest and adopt AI, with higher financing costs expected to reduce AI adoption. In the analysis, the cost of financing variable is proxied by the weighted average lending rate on new loans with maturities exceeding two years, with weights corresponding to the outstanding loan amounts.[4] In our data sample, the average value and standard deviation of financing costs amount to 4.0% and 1.7 pp respectively.

Market concentration

The analysis also considers market concentration as a possible determinant of AI adoption. The expected relationship is theoretically ambiguous. On the one hand, more concentrated markets may enable firms to pass the costs of AI adoption on to consumers, reducing the financial burden of AI-related investments. On the other, firms may have less incentives to innovate, improve efficiency or adopt AI, given relatively greater market power in more concentrated markets. Concentration is computed as the share of net turnover by large firms (250+ employees) relative to the total, with an average of 33.2% and a standard deviation of 21.2 pp in our sample.

4 Empirical Methodology

4.1 Baseline specification

To examine the potential drivers of AI adoption, we leverage on the empirical strategy used by Misch et al. (2025) and Brey & van der Marel (2024). While they analyse the drivers of AI adoption by applying cross-section regression, we estimate a panel regression model of the following form:

$$AI_{i,j,t} = \alpha_{\mathrm{i}} + \gamma_j + \delta_t + \beta X_{i,j,t-1} + \epsilon_{i,j,t}$$

where $AI_{i,j,t}$ denotes the AI adoption rate in country *i,* industry *j* and year *t.* $X_{i,j,t-1}$ is a vector of lagged explanatory variables to alleviate the potential reverse causality concern and α_{i}, $\gamma_{j,}$ and δ_t denote country, industry and year fixed effects respectively. Lagged explanatory variables are used due to limited immediate simultaneity and to capture the delayed effect on AI adoption. Fixed effects remove many transitory confounders: country fixed effects capture persistent national characteristics (institutional environment, culture, baseline digital readiness, regulatory frameworks), industry fixed effects account for persistent sectoral differences (automation potential, skill needs, data intensity) and year fixed effects capture common global shocks (release of new foundation models, macro cycle, energy shocks). Consistent with the fixed-effects regression framework, the estimated coefficients capture the association between

and lighting systems to actual demand and environmental conditions, while AI-based quality control can reduce material waste, defective products and the energy required for reprocessing.

[4] Lending rates on new loans are obtained from AnaCredit.

changes in structural country–sector characteristics and AI adoption, controlling for time-invariant country and industry heterogeneity and common yearly shocks.

4.2 Alternative specification: A two-way fixed effects model

In the baseline specification proposed model with separate country and industry fixed effects controls for average differences across countries and sectors, but it does not absorb fixed country–sector specific characteristics. In particular, it does not absorb that manufacturing in Germany may have persistently different AI adoption potential than manufacturing in Slovenia, beyond the average Germany effect and the average manufacturing effect. Since AI adoption may be shaped by persistent country–sector factors, such as sectoral specialisation, technology readiness or institutional support in a particular industry, the following panel specification with country–industry fixed effects and year fixed effects is also considered:

$$AI_{i,j,t} = \alpha_{\mathrm{i,j}} + \delta_t + \beta X_{i,j,t-1} + \epsilon_{i,j,t}$$

The alternative specification estimates a two-way fixed effects panel model at the country–industry–year level. Country–industry fixed effects $\alpha_{\mathrm{i,j}}$ control for time-invariant heterogeneity across country–sector pairs, while year fixed effects δt absorb shocks common to all countries and sectors in a given year. The coefficients on lagged explanatory variables therefore capture whether changes in structural drivers within a given country–industry pair are associated with subsequent changes in AI adoption rates.

5 Results

This section presents the main empirical findings. First, we analyse the relationship between lagged labour compensation and AI adoption, assuming different granularities of fixed effects. Then we examine several other possible determinants of AI adoption to provide more robust results and to establish a more credible causal interpretation.

5.1 Labour costs and AI adoption

Table 1 shows the results from estimating the significance of the linear relationship between AI adoption and lagged labour compensation, controlling for different sets of fixed effects. We report estimates from the specification without fixed effects to the specification with the most granular fixed effects.

The coefficient on the lagged labour compensation variable is positive and statistically significant across all specifications. Focusing on the estimates in column (3), a one euro increase in labour compensation is associated with an increase of approximately 0.34 pp in AI adoption, conditional on country, sector and time fixed effects. The result is consistent with standard factor substitution theory and empirical evidence on automation: higher labour costs incentivise firms to adopt AI technologies to reduce reliance on labour. The decline in the coefficient from 0.66 to 0.34 after introducing time fixed effects indicates that part of the cross-sectional relationship may reflect broader time

trends affecting both wages and AI adoption simultaneously, such as technological progress, digitalisation policies or post-pandemic restructuring.

The model with country–industry and time fixed effects in column (4) seems to have issues with overfitting due to overly granular FE. The coefficient on past labour compensation becomes implausibly large and slightly more unstable compared with the baseline model specifications with less granular FE. We conclude that this model may be too saturated, making estimates noisy and sensitive. The model with separate country, sector and time fixed effects in column (3) is therefore considered as our preferred specification in the remainder of the paper.

Table 1: **Labour costs and AI adoption**

	(1)	(2)	(3)	(4)
Constant	0.49			
	(1.60)			
Labour compensation (t-1)	0.59***	0.66***	0.34***	1.20**
	(0.11)	(0.19)	(0.11)	(0.52)
Fixed effects				
country FE	No	Yes	Yes	No
industry FE	No	Yes	Yes	No
country–industry FE	No	No	No	Yes
time FE	No	No	Yes	Yes
Number of countries	20	20	20	20
Number of sectors	10	10	10	10
Number of observations	736	736	736	728
R2	0.33	0.66	0.78	0.88
Within R2	–	0.128	0.052	0.081

Sources: Eurostat, own estimates.
Note: The table reports the estimated effects of lagged labour compensation on AI adoption, applying different model specifications. Labour compensation includes wages and salaries as well as employers' social contributions, measured in euros per hour. The dependent variable AI adoption rate is expressed as the share of firms within each country–industry using at least one type of AI technology. The unit of observation is the country–industry–year level. The sample comprises euro area countries over the period 2021–2025, excluding 2022. Standard errors, clustered at the country–industry level, are shown in parentheses below the respective coefficient estimate. Significance: *** p<0.01, ** p<0.05, * p<0.1.

The above estimates exploit variation within the panel rather than differences in average levels across countries. While substantial cross-country heterogeneity may limit the extent to which the estimated average relationship is representative of individual countries, the results in column (3) do not appear to be driven by any single country.[5] In a leave-one-country-out exercise, the estimated coefficient remains positive and statistically significant in all specifications, ranging from 0.28 to 0.42, compared with the preferred baseline estimate of 0.34.

[5] If there are large differences in levels, variation or sample composition across countries, the estimated coefficient may disproportionately reflect countries with greater within-country variation. A coefficient that looks strong for the full panel may disappear when particular countries are excluded.

5.2 Other possible determinants of AI adoption

The baseline specification likely omits other key determinants of AI adoption. In order to provide more credible evidence on the significance of the relationship between labour compensation and AI adoption, other possible determinants of AI adoption are considered in the subsequent estimations.

Labour market conditions

Table 2 shows the results from estimating the significance of linear relationship between AI adoption and lagged labour compensation, controlling for other labour market conditions.

Table 2: **Labour market-related indicators**

	(1)	(2)	(3)
Labour compensation (t-1)	0.34**	0.36***	0.34***
	(0.11)	(0.11)	(0.11)
Labour productivity (t-1)	0.0007		
	(0.009)		
Job vacancy rate (t-1)		-0.63	
		(0.41)	
ICT employment (t-1)			1.3
			(1.6)
Fixed effects			
country FE	Yes	Yes	Yes
industry FE	Yes	Yes	Yes
time FE	Yes	Yes	Yes
Number of countries	20	20	20
Number of sectors	10	10	10
Number of observations	736	718	736
R2	0.78	0.78	0.78
Within R2	0.052	0.067	0.054

Sources: Eurostat, own estimates.
Note: The table reports the estimated effects of lagged labour compensation on AI adoption, separately controlling for lagged labour productivity, job vacancy rate and ICT employment. Labour compensation includes wages and salaries as well as employers' social contributions, measured in euros per hour. Labour productivity is the amount of real output produced for each hour worked. The job vacancy rate is defined as the share of all posts that are vacant within each country–sector and ICT specialist employment is defined as the share of employed ICT specialists in total employment, varying only at the country level. The dependent variable AI adoption rate is expressed as the share of firms within each country–industry using at least one type of AI technology. The unit of observation is the county–industry–year level. The sample comprises euro area countries over the period 2021–2025, excluding 2022. Standard errors, clustered at the country–industry level, are shown in parentheses below the respective coefficient estimate. Significance: *** p<0.01, ** p<0.05, * p<0.1.

Labour productivity

Controlling for labour productivity does not materially affect the estimated coefficient on labour compensation, and the productivity measure itself is not statistically significant once fixed effects are included. This suggests that the positive relationship between labour costs and AI adoption is not driven by underlying productivity differences across countries or sectors.

Job vacancy rate

The estimates suggest there is no statistically significant evidence that the job vacancy rate is systematically related to AI adoption in our preferred estimation. The insignificant coefficient may also indicate that the job vacancy rate is too broad a measure to capture the specific skill shortages relevant for AI adoption. In particular, job vacancy rates may capture not only shortages in substitutable labour, but also demand for the complementary high-skilled workers required for AI adoption. Nevertheless, the coefficient on past labour compensation remains positive and statistically significant.

Employed ICT specialists and ICT specialist recruitment

The relationship between ICT employment and AI adoption appears positive but insignificant. The relatively short time dimension and strong persistence in both ICT employment and AI adoption may make it difficult to significantly identify their relationship in a specification with extensive fixed effects. Overall, the findings suggest that higher labour costs are robustly associated with stronger AI adoption. Similar estimates are obtained if ICT employment is replaced by ICT specialist recruitment.

Digital skills, education and infrastructure

Table 3 shows the results from estimating the significance of the linear relationship between AI adoption and lagged labour compensation, controlling for education, digital skills and infrastructure.

Digital intensity

The lagged labour compensation still has a positive and significant effect, but it is slightly smaller once digital intensity is controlled for. Lagged digital intensity is positive and highly significant, implying that sectors and countries with a larger share of digitally advanced firms tend to record higher AI adoption rates. The finding is also consistent with the persistence of AI adoption, as the index also incorporates the use of AI technologies.

ICT training

After controlling for country–industry-level ICT training, the effect of lagged labour compensation remains positive, broadly similar in magnitude and statistically significant. Moreover, lagged ICT training has a positive and statistically significant effect, suggesting that past ICT training is an important determinant of AI adoption and may proxy for firms' management readiness and organisational capacity to implement AI. The result is consistent with the findings highlighted by Bick et al. (2026b) and OECD/BCG/INSEAD (2025). Although ICT training is included with the lag, reverse causality may still be a concern which is addressed in Section 5.5.

Education level

By contrast, specification (3) indicates no statistically significant relationship between the broader education level and AI adoption. This suggests that AI adoption may depend more strongly on specialised digital skills, technical capabilities and firm-level digital readiness than on broad measures of education. However, this result is consistent with the findings emphasised by Misch et al. (2025) that industries with more educated workers are more likely to adopt AI because of the higher wages and not because of more educated workers having higher capabilities of developing and using AI technologies.

Table 3: **Digital skills, education and infrastructure**

	(1)	(2)	(3)
Labour compensation (t-1)	0.36***	0.35**	0.34***
	(0.09)	(0.13)	(0.10)
Digital intensity (t-1)	0.12***		
	(0.05)		
ICT training (t-1)		0.25***	
		(0.05)	
Education level (t-1)			0.07
			(0.40)
Fixed effects			
country FE	Yes	Yes	Yes
industry FE	Yes	Yes	Yes
time FE	Yes	Yes	Yes
Number of countries	20	20	20
Number of sectors	10	10	10
Number of observations	690	485	736
R2	0.79	0.81	0.78
Within R2	0.087	0.11	0.052

Sources: Eurostat, own estimates.
Note: The table reports the estimated effects of lagged labour compensation on AI adoption, separately controlling for lagged digital intensity, ICT training and education level. Labour compensation includes wages and salaries as well as employers' social contributions, measured in euros per hour. Digital intensity is defined as the share of firms that are classified as having a high or very high digital level. ICT training is defined as the share of firms providing training to their personnel to develop their ICT skills and education level is expressed as the share of employed persons with tertiary education. The dependent variable AI adoption rate is expressed as the share of firms within each country–industry using at least one type of AI technology. The unit of observation is the county–industry–year level. The sample comprises euro area countries over the period 2021–2025, excluding 2022. Standard errors clustered at the country–industry level are shown in parentheses below the respective coefficient estimate. Significance: *** p<0.01, ** p<0.05, * p<0.1.

Costs and market concentration

Table 4 shows the results from estimating the significance of the linear relationship between AI adoption and lagged labour compensation, controlling for market concentration and energy costs.

Energy costs

The estimates reported in Table 4 column (2) indicate a positive and statistically significant coefficient on lagged energy costs. This suggests that firms facing elevated energy costs may adopt AI technologies to improve operational efficiency or reduce production costs, consistent with a potential cost-efficiency mechanism. The stability and statistical significance of the labour compensation coefficient after including energy costs further supports the interpretation that labour cost pressures are associated with AI adoption independently of other production cost channels.

Financing costs

After controlling for country, industry and time fixed effects, we find no robust evidence of a statistically significant relationship between lending rates and AI adoption. However, the effect of financing costs may depend on how firms implement AI, particularly whether they develop AI solutions internally or acquire and adapt them from external providers.

Market concentration

In specification (1), the coefficient on lagged market concentration is negative but statistically insignificant, potentially reflecting the coexistence of opposing mechanisms highlighted in Section 3. Nevertheless, the negative sign could indicate that firms operating in more competitive environments may face stronger incentives to innovate, improve efficiency and adopt AI technologies in order to maintain competitiveness and reduce costs.

Table 4: **Energy costs, financing costs and market concentration**

	(1)	(2)	(3)
Labour compensation (t-1)	0.34**	0.34**	0.33**
	(0.10)	(0.10)	(0.12)
Energy costs (t-1)	14.4**		
	(5.8)		
Financing costs (t-1)		0.22	
		(0.77)	
Market concentration (t-1)			-0.06
			(0.04)
Fixed effects			
country FE	Yes	Yes	Yes
industry FE	Yes	Yes	Yes
time FE	Yes	Yes	Yes
Number of countries	20	20	20
Number of sectors	10	10	10
Number of observations	736	736	524
R2	0.78	0.78	0.83
Within R2	0.054	0.054	0.057

Sources: Eurostat, own estimates.
Note: The table reports the estimated effects of lagged labour compensation on AI adoption, separately controlling for market concentration, energy costs and financing costs. Labour compensation includes wages and salaries as well as employers' social contributions, measured in euros per hour. Market concentration is computed as the share of net turnover by large firms (250+ employees) relative to the total. The energy costs variable is measured by electricity prices for non-household consumers (band 2 000–19 999 MWh), including taxes, in EUR per kilowatt-hour, varying only across countries. The financing costs variable is computed as the weighted average lending rate on new loans with maturities exceeding two years, with weights corresponding to the outstanding loan amounts. The dependent variable AI adoption rate is expressed as the share of firms within each country–industry using at least one type of AI technology. The unit of observation is the county–industry–year level. The sample comprises euro area countries over the period 2021–2025, excluding 2022. Standard errors clustered at the country–industry level are shown in parentheses below the respective coefficient estimate. Significance: *** p<0.01, ** p<0.05, * p<0.1.

5.3 Consolidated results and synthesis

Table 5 presents the consolidated results, incorporating all potential determinants of AI adoption considered in the analysis. Across all specifications, the coefficient on lagged labour compensation remains positive, relatively stable and statistically significant, suggesting that higher labour costs are associated with faster AI adoption, consistent with a cost-efficiency mechanism.

Table 5: **Consolidated results**

	(1)	(2)	(3)	(4)	(5)
Labour compensation (t-1)	0.34**	0.35**	0.35**	0.30*	0.36*
	(0.10)	(0.11)	(0.13)	(0.13)	(0.18)
Energy costs (t-1)	14.4**	9.8	22.8	2.3	15.1
	(5.8)	(7.1)	(14.5)	(11.4)	(22.8)
Digital intensity (t-1)		0.12***		0.12***	
		(0.03)		(0.03)	
ICT training (t-1)			0.25***		0.22**
			(0.05)		(0.09)
Labour productivity (t-1)				0.03	0.02
				(0.02)	(0.01)
Job vacancy rate (t-1)				-0.78	-0.93
				(0.52)	(0.64)
Education level (t-1)				-0.10	0.09
				(0.43)	(0.84)
Market concentration (t-1)				-0.12	-0.15
				(0.10)	(0.12)
Financing costs (t-1)				-0.05	0.09
				(0.72)	(0.84)
Fixed effects					
country FE	Yes	Yes	Yes	Yes	Yes
industry FE	Yes	Yes	Yes	Yes	Yes
time FE	Yes	Yes	Yes	Yes	Yes
Number of countries	20	20	20	20	20
Number of sectors	10	10	10	9	9
Number of observations	736	690	485	482	317
R2	0.78	0.79	0.81	0.85	0.84
Within R2	0.05	0.088	0.11	0.13	0.15

Sources: Eurostat, own estimates.
Note: The table reports consolidated results, including all considered potential determinants of AI adoption rates. ICT training and digital intensity are considered separately, as ICT training at least to some extent overlaps conceptually with digital intensity, causing part of its explanatory power to be absorbed by the digital intensity indicator.[6] For the same reasons, ICT employment is excluded. The unit of observation is the county–industry–year level. The sample comprises euro area countries over the period 2021–2025, excluding 2022. The sample size varies across specifications due to missing observations. Standard errors clustered at the country–industry level are shown in parentheses below the respective coefficient estimate. Significance: *** p<0.01, ** p<0.05, * p<0.1.

In general, we do not find robust evidence for labour productivity, job vacancy rate, ICT employment and education level. The coefficient on energy costs becomes statistically insignificant (columns (2) and (3)) once we control for digital intensity or ICT training.[7] However, energy costs primarily vary at the country level, thus the remaining identifying variation after the inclusion of granular fixed effects and additional controls becomes relatively limited, reducing estimation precision. Moreover, one should remain cautious when interpreting results, as the sample size is notably smaller, especially in columns (3), (4) and (5).

[6] We consider ICT training and digital intensity in separate specifications due to their high correlation (0.86), while education is only weakly correlated with digital intensity and ICT training (0.09 and 0.06 respectively), suggesting limited concerns about multicollinearity.

[7] We also estimate the model using energy cost exposure, measured as electricity expenditure relative to net turnover, instead of energy costs. Energy cost exposure remains positively and statistically significantly associated with AI adoption also after controlling for digital intensity and ICT training. However, the coefficient becomes statistically insignificant when all other potential determinants of AI adoption considered in the analysis are included. Given these inconclusive findings, we retain energy costs in the main model specification, as constructing a consistent and comparable measure of energy cost exposure across euro area countries and industries is constrained by data availability and differences in sectoral coverage.

5.4 Labour costs and AI exposure

We next examine whether the identified labour-cost channel varies with sectoral AI exposure by interacting lagged labour compensation with sectoral AI exposure. The underlying hypothesis is that higher labour costs provide stronger incentives for AI adoption in industries where a larger share of tasks can potentially be automated, transformed or complemented by AI technologies. Conversely, labour-cost pressures may have a more limited effect in industries where the technological applicability of AI is lower.

Table 6: **Labour costs and sectoral AI exposure**

	(1)	(2)	(3)
Constant	-10.8		
	(7.5)		
Labour compensation (t-1)	-0.40	0.53*	-0.35*
	(0.43)	(0.25)	(0.19)
AI exposure (t-1)	57.6*	-23.0	-38.9***
	(26.9)	(13.8)	(8.1)
Labour compensation x AI exposure (t-1)	2.5*	0.40	1.8**
	(1.3)	(0.76)	(0.62)
Fixed effects			
country FE	No	Yes	Yes
industry FE	No	Yes	Yes
time FE	No	No	Yes
Number of countries	20	20	20
Number of sectors	10	10	10
Number of observations	722	722	722
R2	0.47	0.66	0.78
Within R2	–	0.13	0.077

Sources: Eurostat, own estimates.
Note: The table reports estimates of the relationship between lagged labour compensation and AI adoption, allowing this relationship to vary with sectoral AI exposure. Sectoral AI exposure is constructed by combining occupation-level generative AI exposure scores from Gmyrek et al. (2025) with Eurostat employment data by occupation and industry. The dependent variable is the share of firms using at least one AI technology. The unit of observation is the country–industry–year. The sample covers 20 euro area countries and ten industries over 2021–2025, excluding 2022. Standard errors clustered at the country–industry level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table 6 reports the results from specifications including the interaction between lagged labour compensation and sectoral AI exposure. The interaction term is positive and statistically significant in the preferred specification with country, industry and year fixed effects. This suggests that the relationship between labour costs and AI adoption is stronger in industries with greater technological exposure to AI, consistent with higher labour costs creating stronger incentives for adoption where AI has broader potential applicability. Since the specification includes an interaction term, the individual coefficients on labour compensation and AI exposure represent conditional effects and should not be interpreted independently.

Table 7: **Labour costs and AI exposure – Consolidated specifications**

	(1)	(2)
Labour compensation (t-1)	-0.75***	-0.84***
	(0.17)	(0.21)
Energy costs (t-1)	3.8	14.6
	(12.9)	(25.0)
Digital intensity (t-1)	0.14***	
	(0.04)	
ICT training (t-1)		0.26**
		(0.11)
Labour productivity (t-1)	0.03	0.01
	(0.02)	(0.02)
Job vacancy rate (t-1)	-1.0*	-1.2*
	(0.52)	(0.64)
Education level (t-1)	-0.09	0.14
	(0.46)	(0.80)
Market concentration (t-1)	-0.10	-0.13
	(0.10)	(0.11)
Financing cost (t-1)	0.05	0.25
	(0.72)	(0.85)
AI exposure (t-1)	-78.3***	-84.1***
	(11.3)	(12.0)
AI exposure x Compensation (t-1)	2.7***	3.1***
	(0.54)	(0.55)
Fixed effects		
country FE	Yes	Yes
industry FE	Yes	Yes
time FE	Yes	Yes
Number of countries	20	20
Number of sectors	9	9
Number of observations	481	317
R2	0.86	0.85
Within R2	0.19	0.21

Sources: Eurostat, Gmyrek et al. (2025), and own calculations.
Note: The table reports consolidated estimates of the relationship between lagged labour compensation and AI adoption, allowing this relationship to vary with sectoral AI exposure. Sectoral AI exposure is constructed by combining occupation-level generative AI exposure scores from Gmyrek et al. (2025) with Eurostat employment data by occupation and industry. Digital intensity and ICT training are included separately because of their conceptual overlap. The unit of observation is the country–industry–year. The sample covers 20 euro area countries and ten industries over 2021–2025, excluding 2022. Standard errors clustered at the country–industry level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table 7 reports consolidated specifications that retain the interaction between lagged labour compensation and sectoral AI exposure. These specifications also control for a broader set of variables. The interaction term remains positive and statistically significant in both specifications, indicating that the relationship between labour costs and AI adoption depends strongly on the technological applicability of AI within the sector. At low levels of AI exposure, higher labour compensation is not associated with stronger adoption. As AI exposure increases, however, the marginal effect of labour compensation becomes progressively more positive. Based on the estimated coefficients, the relationship turns positive when the exposure index exceeds approximately 0.27 in both specifications.[8] This suggests that higher labour costs encourage AI adoption primarily

[8] Within our sample, all sectors except construction have a euro area average AI exposure above the estimated threshold of 0.27. Construction records an average exposure score of approximately 0.24. This indicates that the marginal effect of labour compensation is positive for the large majority of industries in the sample, although the aggregate industry averages may mask variation across individual country–industry observations.

in industries where the occupational task structure provides meaningful scope for AI-based automation or augmentation. Digital intensity and ICT training also remain positively associated with AI adoption, while most other explanatory variables are not statistically significant.

5.5 Robustness and reverse causality identification

Dynamic panel specification

The baseline specification does not include lagged AI adoption, as the objective is to assess the relationship between structural drivers and observed adoption rates. However, given the persistence and path-dependence of AI adoption, specifications including lagged AI adoption are estimated as an additional robustness check. The dynamic panel specification assesses whether the proposed drivers explain AI adoption beyond its own past dynamics:

$$AI_{i,j,t} = \alpha_{\mathrm{i}} + \gamma_j + \delta_t + \beta X_{i,j,t-1} + \rho AI_{i,j,t-1} + \epsilon_{i,j,t}$$

Table 8: **Dynamic panel specification**

	(1)	(2)	(3)
Constant	1.60		
	(0.94)		
Labour compensation (t-1)	0.11***	0.11***	0.12***
	(0.03)	(0.03)	(0.03)
AI adoption (t-1)	1.1***	0.79***	0.70***
	(0.05)	(0.07)	(0.06)
Fixed effects			
country FE	No	Yes	Yes
industry FE	No	Yes	Yes
time FE	No	No	Yes
Number of countries	20	20	20
Number of sectors	10	10	10
Number of observations	359	359	359
R2	0.89	0.94	0.95
Within R2	–	0.610	0.479

Sources: Eurostat, own estimates.
Note: The table reports the estimated effects of lagged labour compensation on AI adoption, controlling for lagged AI adoption. Labour compensation includes wages and salaries as well as employers' social contributions, measured in euros per hour. The dependent variable AI adoption rate is expressed as the share of firms within each country–industry using at least one type of AI technology. The unit of observation is the county–industry–year level. The sample comprises euro area countries over the period 2021–2025, excluding 2022. Standard errors clustered at the country–industry level are shown in parentheses below the respective coefficient estimate. Significance: *** p<0.01, ** p<0.05, * p<0.1.

The dynamic specification yields smaller coefficients on labour compensation, consistent with the idea that part of its effect operates through persistence in AI adoption. However, given the short time dimension of the panel, the obtained estimates are subject to Nickell bias and should be interpreted with caution. For these reasons, the static fixed effects model is preferred, while dynamic specification is treated as a complementary robustness check that highlights the importance of persistence rather than providing unbiased estimates of structural effects.

Reverse causality diagnostics

In our empirical setting, the use of lagged explanatory variables together with detailed fixed effects helps reduce concerns about contemporaneous reverse causality. However, it may not be entirely eliminated if firms adjust wages, ICT training and AI adoption jointly over time, i.e. more productive, innovative and technologically advanced firms may simultaneously adopt AI, offer higher wages and conduct more ICT trainings.

We therefore perform two robustness tests. First, to assess possible reverse causality, we regress labour costs on lagged AI adoption:

$$LC_{i,j,t} = \alpha_{\mathrm{i}} + \gamma_j + \delta_t + \beta AI_{i,j,t-1} + \epsilon_{i,j,t}$$

where $LC_{i,j,t}$ denotes labour costs, measured as compensation per employee per hour worked. The results in Table 9 show that the coefficient becomes statistically insignificant once country and industry fixed effects are included and remains insignificant after controlling for year fixed effects. This suggests that reverse causality is unlikely to drive the baseline results, although omitted variables and simultaneous determination cannot be fully ruled out.

Table 9: **Reverse causality diagnostics i)**

	(1)	(2)	(3)
Constant	19.0*** (2.60)		
AI adoption (t-1)	0.76*** (0.184)	0.18 (0.135)	0.15 (0.123)
Fixed effects			
country FE	No	Yes	Yes
industry FE	No	Yes	Yes
time FE	No	No	Yes
Number of countries	20	20	20
Number of sectors	10	10	10
Number of observations	369	369	369
R2	0.28	0.84	0.87
Within R2	–	0.030	0.021

Sources: Eurostat, own estimates.
Note: The table reports estimates from reverse-causality specifications in which labour compensation is regressed on lagged AI adoption. Labour compensation includes wages and salaries and employers' social contributions and is measured in euros per employee per hour worked. AI adoption is expressed as the share of firms within each country–industry using at least one AI technology. The unit of observation is the country–industry–year. The sample covers euro area countries over the period 2021–2025, excluding 2022. Standard errors clustered at the country–industry level are reported in parentheses below the coefficient estimates. Significance: *** p<0.01, ** p<0.05, * p<0.1.

As a second robustness test, we regress AI adoption on labour compensation and ICT training measured in 2015, before the widespread adoption of AI technologies:

$$AI_{i,j,t} = \alpha_{\mathrm{i}} + \gamma_j + \delta_t + \beta X_{i,j,2015} + \epsilon_{i,j,t}$$

The results in Table 10 provide relatively strong evidence that the positive relationship between labour compensation and AI adoption is not driven purely by contemporaneous reverse causality. Since labour compensation is measured in 2015, before the widespread adoption of generative AI, it is less plausible that AI adoption itself influenced wage levels at that time. The coefficient of 0.35, significant at 5%, suggests that

sectors and countries with higher pre-existing labour compensation subsequently exhibited higher AI adoption rates.

Table 10: **Reverse causality diagnostics ii)**

	(1)	(2)	(3)
Labour compensation (2015)	0.35**		0.26***
	(0.12)		(0.02)
ICT training (2015)		0.30***	0.17
		(1e-6)	(0.10)
Fixed effects			
country FE	Yes	Yes	Yes
industry FE	Yes	Yes	Yes
time FE	Yes	Yes	Yes
Number of countries	20	20	20
Number of sectors	10	7	7
Number of observations	736	537	537
R2	0.77	0.86	0.86
Within R2	0.033	0.053	0.059

Sources: Eurostat, own estimates.
Note: The table reports the estimated effects of labour compensation (2015) and ICT training (2015) on AI adoption. Labour compensation includes wages and salaries as well as employers' social contributions, measured in euros per hour. ICT training is defined as the share of firms providing training to their personnel to develop their ICT skills. The dependent variable AI adoption rate is expressed as the share of firms within each country–industry using at least one type of AI technologies. The unit of observation is the county–industry–year level. The sample comprises euro area countries over the period 2021–2025, excluding 2022. Standard errors clustered at the country–industry level are shown in parentheses below the respective coefficient estimate. Significance: *** p<0.01, ** p<0.05, * p<0.1.

When considered separately (column (2)), ICT training displays a strong and statistically significant relationship with AI adoption, suggesting that pre-existing investments in digital skills facilitate the adoption of AI technologies. However, once labour compensation is included (column (3)), the coefficient on ICT training becomes statistically insignificant, while labour compensation remains significant. The loss of significance for ICT training in column (3) may result from a strong correlation between ICT training and labour compensation, as more skilled workers tend to earn higher wages.

6 Policy Implications and Conclusion

This analysis examines the structural determinants of AI adoption across euro area countries and industries. The results provide robust evidence of labour-cost-driven AI adoption, consistent with an economic mechanism for automation and labour substitution. Across all specifications, lagged labour compensation remains positive and statistically significant, suggesting that higher labour costs are associated with faster AI adoption. The coefficient declines after introducing country, sector and time fixed effects, indicating that part of the raw correlation reflects structural sectoral differences and common time trends, i.e. sectors with structurally high wages (e.g. finance, ICT and pharma) also having high AI use. The reverse causality diagnostics strengthen the interpretation that higher labour costs act as a determinant, rather than a consequence, of AI adoption.

The analysis further shows that the labour-cost channel is considerably stronger in sectors with greater technological exposure to AI. This suggests that firms respond most strongly when the economic incentives for adoption coincide with greater scope for AI to automate, transform or complement the tasks performed within the sector. Digital intensity and ICT training also emerge as important predictors of AI adoption, capturing the technological and organisational capabilities required for AI adoption. By contrast, there is no robust evidence that labour productivity, labour market tightness, education level, energy costs and market concentration independently explain AI adoption, once country, industry and year heterogeneity are taken into account.

These results also have policy implications. First, human capital remains an important complement to AI technologies, even where automation reduces demand for certain tasks or occupations. The positive association between ICT training and AI adoption suggests that firms' ability to implement AI depends not only on technological exposure, but also on the availability of relevant skills and organisational capabilities. Second, policies that support retraining and upskilling can facilitate workers' transition towards AI-complementary tasks and help translate broader adoption of AI technologies into productivity gains.

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