Artificial Intelligence: what drives adoption in EU countries?

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Abstract

This paper uses results from successive waves of the Eurostat survey on 'ICT usage and e-commerce in enterprises' to study the determinants of AI adoption in a country/industry/time panel covering 15 countries and 24 industries of the European Union over 2021–2025. We relate adoption to several potential drivers: the perceived obstacles to adoption, the business environment (such as investment in organizational capital), the policy context (such as policies affecting the capabilities and incentives to adopt and use AI technologies) and demography (shares of different age groups within employees). We summarize some of the potential drivers using Principal Components Analyses and take a diff-in-diff approach to highlight how the influence of nation-wide drivers of adoption differs depending on industry exposure to them. We find robust statistical associations of both adoption and the extent of AI use (at least three AI technologies) with mismatch obstacles (data availability, expertise, technological incompatibility, or AI's perceived lack of usefulness for the firm) whose significance has increased over time, as well as with costs and personal concerns (legal uncertainty, ethical and privacy concerns) whose significance has decreased over time. Human capabilities (such as ICT skills and organizational capital) and innovation policies are positively related to AI adoption, while policies curbing either workforce flexibility or competition in industries that are key providers of intermediate inputs are inversely related to adoption. Finally, we find evidence of an inverted U-curve between workforce age and AI adoption, with adoption being weaker where the age distribution is tilted towards young or elderly workers; however, higher AI exposure in an industry moderates these demographic effects, perhaps due to skill leveling effect of the new technology.

1. INTRODUCTION

There is a rising consensus that AI is a new General Purpose Technology (GPT) whose rapid diffusion is desirable because it could boost lingering productivity growth in both advanced and emerging economies (Aghion et al., 2019; Brynjolfsson et al., 2019; Crafts, 2021; Filippucci et al., 2024, 2026; Calvino et al., 2025). While estimates of future aggregate productivity gains are highly uncertain and span a wide range — from 0.1% (Acemoglu, 2025) to 1.5% (Aghion and Bunel, 2024) or even 2.5% (McKinsey, 2023) per year — most analysts find significant productivity gains at the worker or firm level (e.g. Noy and Zhang, 2023; Da Silva Marioni et al., 2024; Brynjolfsson et al., 2023). Equally important is the speed and distributional pattern of diffusion: adoption has been faster than for previous GPTs overall (Bick et al., 2024; Allen, 2026), but highly uneven across countries, industries and firms (McElheran et al., 2024; Allen, 2026; Calvino et al., 2026; Ropele and Tagliabracci, 2026; Pulito et al., 2026).

This paper provides an empirical investigation of the industry-specific drivers of AI adoption across a large set of European countries. It draws on successive waves of the Eurostat Survey on 'ICT usage and e-commerce in enterprises', which includes since 2021 information on the share of firms adopting a range of AI technologies in each manufacturing or service industry as well as the perceived obstacles to such adoption.[1] We supplement this database with additional information concerning structural, policy and other characteristics that may affect adoption. The resulting panel covers 15 EU countries and 24 industries, with adoption and perceived obstacles spanning the 2021-25 period.[2]

Our analysis joins a nascent line of research exploring the factors that may explain differences in AI adoption across countries or sectors. It contributes to it in three main ways. First, we exploit the information about perceived obstacles compiled in the Eurostat survey, which has been previously overlooked. Second, while earlier research has focused mainly on socio-economic factors such as industry composition, firm size or skills (McElheran, 2024; Garbers & Gregory, 2026; Pulito et al., 2026), we extend the focus to the availability of complementary intangibles (such as organizational capital or digital access) and public policy influences. Third, we provide the first systematic cross-country/cross-sectoral analysis of the link between AI adoption and the workforce age distribution.[3]

The Eurostat Survey reports adoption of seven different types of AI technologies.[4] Throughout the analysis, we distinguish between adoption of any kind and number of AI technologies ("adoption") and adoption of at least three types of AI technologies ("extensive" adoption). Building on the approach to drivers of digital adoption by Nicoletti et al. (2020), factors explaining AI adoption and extensive AI adoption are organised into sectoral 'capabilities' and

[1] The survey covers 157,000 enterprises with at least 10 employees and self-employed from all EU Member States, Iceland and Norway as well as candidate countries. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Use_of_artificial_intelligence_in_enterprises#Data_sources

[2] A slightly larger sample, including 17 countries can be considered by omitting obstacles from the analysis. The corresponding results are shown in the Annex.

[3] We are aware of only two other studies that come close to some dimensions of our analysis. André & Schief (2026) use OECD data from the Survey of adult skills (PIAAC) to relate AI exposure to demographic characteristics of the workforce. Bick et al. (2026) relate adoption rates from the Eurostat Survey to the Bloom & van Reenen (2010) cross-country measures of managerial quality.

[4] An eighth AI type was added in the 2025 wave of the Survey. We take this into account in cross-section regressions focusing on the year 2025.

'incentives' along with perceived obstacles and demographic variables. Capabilities mainly reflect complementary intangibles assets needed for the use of AI. Incentives relate to policies that directly or indirectly affect adoption choices, such as innovation policies or market regulations, respectively.

Given the large number of factors potentially affecting AI adoption, the analysis is made tractable by summarizing subsets of them by principal component analyses (PCA). This allows grouping adoption drivers into key areas within the perceived obstacles, capabilities and incentives categories, avoiding redundancies and accounting for synergies. Moreover, adoption drivers that are nation-wide, such as some regulations and policies, are interacted with the extent of industry exposure to them.[5] For instance, an industry-specific index of digital intensity is used to measure exposure to regulation of digital markets.

Findings from panel regressions relating various measures of adoption to its potential drivers and other controls (such as average firm size or ICT assets) can be summarized as follows. Across both adoption and extensive adoption, AI take up is most negatively related to contemporaneous perceived obstacles of a 'mismatch' nature, such as lack of access to data and ICT expertise or incompatibility with existing business processes, while (especially extensive) AI use is boosted by the pre-sample intensity of organisational capital, ICT training and support to innovation.[6] The beginning-of-period policy environment is also found to have a significant influence. Anticompetitive product market regulations in upstream industries that are important providers of intermediate inputs, heavy digital market regulations and rigid hiring and firing rules in industries with high workforce turnover are negatively associated with adoption. Regarding demographics, we document an inverted U-curve: adoption is weaker where either young (15–24) or senior (50+) workers predominate, and stronger where prime-age workers (25–49) are most prevalent. This pattern attenuates significantly in industries with high AI exposure, suggesting a skill-levelling effect of the technology in those contexts.

We interpret the results in the following way. First, investing in complementary intangible assets, such as digital skills or managerial competence, seems a key factor for AI adoption. However, more work is needed to establish the direction of causation between perceived obstacles and adoption as increased use of AI over time could raise skill bottlenecks also affecting perceptions of mismatch obstacles by survey respondents. Second, the link between innovation support and extensive AI adoption may reflect increased absorptive capacity related to stronger R&D spending. Third, regulations that thwart competition in key non-manufacturing upstream industries may curb adoption by contributing to raise the cost of producing or using AI technologies (e.g. via high energy and communication costs) and by reducing incentives to use it (e.g. due to lack of competitive pressures in key business services). Fourth, strict employment protection rules may weaken AI adoption especially in high job turnover industries by hindering workforce reorganization upon adoption of the new technology, which also adds to the costs of using it in a profitable way. Finally, especially in industries that are less exposed to AI, adoption is eased by the prevalence of prime-age workers due to their stronger on-the-job experience and lesser fear that their tasks risk being automated. If our interpretations are correct, the findings indicate possible ways in which policy reforms might help accelerate the

[5] See Rajan and Zingales (1998) for an early application of this approach.

[6] There is also suggestive evidence that the negative link with perceived mismatch obstacles has risen over time relative to that of other perceived obstacles (such as excessive cost of AI or uncertainties related to the legal framework and privacy or security issues).

diffusion of AI in EU economies while also pointing to the difficult challenges related to the generalized aging of the EU workforce.

The remainder of the paper proceeds as follows. Section 2 sets out the analytical and empirical framework. Section 3 describes the data and provides descriptive statistics. Section 4 presents the empirical results in three subsections. Section 5 discusses policy implications.

2. Investigating AI adoption: Framework and empirical strategy

Conceptual framework

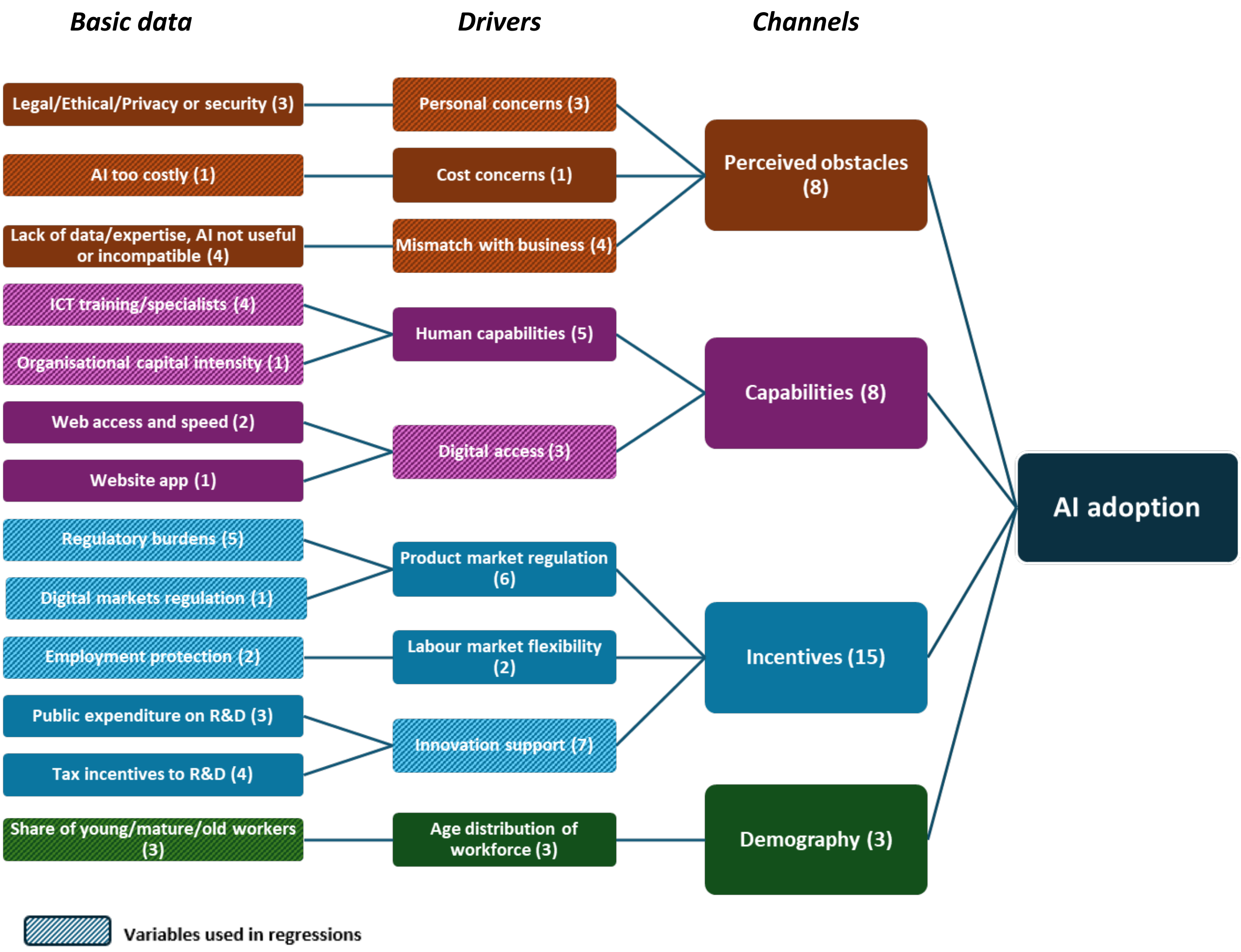
We examine the relationship between the adoption of various AI technologies and its potential drivers, extending the approach proposed by Nicoletti et al. (2020) for the adoption of digital technologies. Figure 1 outlines our conceptual framework, highlighting four main channels: perceived obstacles, capabilities, incentives, and demography. Each driver is implemented empirically drawing on Eurostat surveys (for obstacles, ICT training/specialists and digital access) or on structural and policy indicators from other sources.

When there are multiple indicators for a driver, we summarize the information via Principal Components Analyses (PCA). For instance, 'ICT training/specialists' contains information about (i) the share of firms providing ICT training, (ii) the share of firms employing ICT specialists, (iii) the share of firms that both provide ICT training and employ ICT specialists and (iv) the industry's investment in ICT training (per hour worked): these four indicators are summarized by the first PCA axis. In other cases we rely on single indicators (e.g. for obstacles related to costs) or alternative methodologies (e.g. for regulatory burdens). Details are provided in the next section.

Perceived obstacles include: (i) legal, ethical, privacy and security concerns (henceforth 'personal concerns'); (ii) 'mismatch' obstacles related to data availability, expertise, technological incompatibility, or AI's perceived lack of usefulness for the firm; and (iii) cost concerns. The relevance of personal concerns has been stressed in research relating AI adoption to legal uncertainties, liability risks, and regulatory compliance issues (Filippucci et al., 2024; OECD, 2025; Raji et al., 2020; Novelli et al., 2023; Chen, 2023). Mismatch obstacles capture the complementarity between intangible assets and new technologies, which have been found to be key firm-level impediments to digital adoption (Calvino and Fontanelli, 2023; Corrado et al., 2024; Calvino et al, 2026). Costs are also indirectly related to both mismatch obstacles and personal concerns as assuaging them may require significant investments on behalf of the firms (e.g. acquiring big data, hiring qualified managers and training existing staff, facing regulatory and legal consequences, etc.).[7]

[7] Cost concerns include not only the necessary investments in AI acquisition or development but also the financing of complementary intangibles, which are often hard to pledge as collateral partly due to their uncertain and risky returns (Demmou et al., 2021; Berlingieri et al., 2020; Pisu et al., 2021).

Figure 1. Drivers of AI adoption investigated in the empirical analysis
(number of indicators in parenthesis)



Capabilities include the availability of skills (ICT training, specialists), effective business models (organizational capital), and access to adequate digital infrastructure. These industry characteristics were shown to be key for broader digital adoption, as they increase absorption capacity (Nicoletti et al., 2020) and anticipated productivity gains (Gal et al., 2019).

Incentives to adopt are shaped by many public policies. Here we focus on product market regulations adverse to competition (particularly in upstream industries providing key intermediate inputs), employment protection legislations, digital market regulations, and innovation support policies such as R&D subsidies and tax incentives. Some of these policies tend to either hinder or promote adoption:

- Lack of competition in upstream industries generates rent seeking and inefficiencies that translate into higher costs and less choice for the downstream industries engaged in technology adoption. This can occur, for instance, via higher prices and lower quality of energy, communication and business services or less efficient distribution channels (Bourlès et al., 2013).

- Support for R&D can make AI adoption easier by encouraging experimentation, lowering investment costs and raising absorption capacity more generally (Griffith et al., 2004).

Other policies may have more ambiguous effects on adoption:

- Excessive labor market rigidities, such as those implied by strict job protection rules, can be at odds with the swift workforce changes required by new technologies and *de facto* impose additional costs on adoption (Griffith & Macartney, 2014; Aghion et al., 2023). Moreover, significant rigidities in the labor market, such as costly and complex dismissal procedures, can discourage the use of new technologies whose returns still appear uncertain. Such a result has, for example, been shown by Cette et al. (2018) concerning investment in ICT. However, job protection can also favor the investment in training necessary to successfully absorb AI adoption (Acemoglu & Pischke, 1998; Messe & Rouland, 2014; Aepli et al., 2024).
- Digital market regulations can encourage adoption by providing a clear framework for market interactions (e.g. concerning privacy, data access or transactions in multisided platforms) or discourage adoption by increasing costs, barring entry and stiffening markets (Nicoletti et al., 2023).

Finally, we relate AI adoption to *demography*. The link between age and use of new technologies is conceptually ambiguous and the empirical evidence is inconclusive (Fazi et al., 2025). AI adoption is closely related to its expected returns when replacing or complementing (and augmenting) tasks executed by workers. In turn, task bundles are often related to workers' age in complex ways. In terms of experience, AI tends to be more substitutable or complementary to entry-level tasks, generally executed by young staff (Brynjolfsson et al., 2023 ; Noy & Zhang, 2023; Peng et al., 2023), at the same time often acting as a "skill-leveler" (Dell'Acqua et al., 2023). But AI can also help climb the task ladder for more experienced workers, who are often older, amplifying their role in judgmental and analytical tasks (Hosseini Masoum & Lichtinger, 2025; Choi & Xie, 2025). In terms of skills, higher levels of basic digital literacy, typically prevalent in youth, may encourage adoption by allowing a more productive use of AI. But older workers may also be using AI because natural language interaction and agency facilitate access to complex tasks by lowering the digital skill floor (OECD, 2023).

We investigate the net effects of such conflicting influences at the aggregate level. A few empirical studies have related age to firm-level use of AI technologies highlighting the positive impact of workers' experience, which generally comes at prime age.[8] Other studies have highlighted worker adoption or exposure to AI as a function of age (Bick et al., 2026; André & Schief, 2026).[9] To the best of our knowledge, we are the first to investigate the net effects of age on AI take up by relating sectoral adoption rates to the age distribution of the workforce.

8 Kikushi (2025) focuses on the age of Japanese CEOs finding that those below 50 have a higher propensity to adopt AI in their business. Wolfe et al. (2025) focus on experience and organization level of employees of a multinational firm finding higher acceptance of AI use among more experienced and more senior staff. This finding is also echoed by Pillai et al. (2024) who find that in Korea more experienced staff have a better acceptance of AI use in the workplace.

9 Bick et al. (2026) use their own survey of workers' AI use to report overall usage rates by age in various countries. André & Schief (2026) relate a measure of exposure to AI to individual workers' age using results from the OECD Survey on Adult Skills (PIAAC).

Empirical strategy

We implement the empirical analysis in two steps. First, we summarize both adoption and some of its drivers through Principal Components Analysis (PCA).[10] As the basic information covers multiple AI technologies and several individual drivers of adoption, PCA helps extracting synthetic measures of both adoption and its drivers that explain most of the overall cross-industry/cross-country variance spanned by the data. PCA also allows avoiding overlaps and accounting for synergies among related AI technologies or drivers.

Second, we link AI adoption to the drivers described above, other possible influences (e.g. industry characteristics in each country) and a set of fixed effects via the following specification:

$$AdoptAI_{cit} = \alpha + \sum_j \beta^j * obstacle_{cit}^j + \sum_s \gamma^s * capability_{ci0}^s + \sum_r \delta^r * incentive_{ci0}^r + \sum_v \theta^v * demography_{ci0}^v + \sum_k b^k * control_{ci0}^k + \phi_c + \phi_i + \phi_t + \epsilon_{cit}$$

where for country c, industry i and time t:

- $AdoptAI_{cit}$ is one of three adoption outcomes: the share of surveyed firms not adopting any AI technology; the share of surveyed firms adopting any of the seven AI technologies (the first principal component of the seven individual AI adoption rates); or the share of surveyed firms adopting AI extensively (at least three AI technologies);
- $obstacle_{cit}^j$ is the share of surveyed firms perceiving obstacles to adoption: anticipated costs and the 1st principal components of obstacles related to either personal concerns or mismatches;
- $capability_{cit}^s$ are the drivers related to capabilities (the 1st principal component of four indicators about ICT training and expertise; organizational capital; and the 1st principal component of digital access, speed and web presence);
- $incentive_{cit}^r$ are the drivers related to incentives (the measures of upstream regulatory burdens, digital market regulation, labour market rigidity and the 1st principal component summarizing R&D spending and the indicators of R&D subsidies and tax incentives);
- $demography_{cit}^v$ are the drivers related to demography describing the age distribution of the workforce;
- $control_{cit}^k$ are other potentially relevant time-varying country-industry characteristics; and
- ϕ_c, $\phi_i$and ϕ_t are country, industry and time fixed effects.

While all variables have a time dimension, we keep capability, incentive and demographic drivers predetermined at pre-sample levels.[11] Use of predetermined drivers mitigates

[10] All details about PCA results are available in Annex Table B11.

[11] Nonetheless, our results are qualitatively unchanged when we estimate the model as a full dynamic panel, with lags on all explanatory variables except obstacles (see Annex Table C8).

endogeneity concerns due to reverse causality via political economy channels.[12] It also accounts for lags between the implementation of policies and their effects on markets.

Obstacles are contemporaneous, which introduces some reverse-causality risk as their perception by respondents to the Eurostat Survey may rise with aggregate AI usage. However, instrumenting obstacles using a Bartik (1991) approach leaves results unchanged (see Annex Tables C6).

The fixed effects account for unobserved heterogeneity that could bias the estimates. Country fixed effects control for nation-wide characteristics that may influence AI adoption, such as preferences, cultural bias, institutional quality, the business environment, industry composition or overall digital literacy. Industry fixed effects absorb industry characteristics potentially relevant for AI adoption that are common across countries, such as ICT intensity, AI exposure, knowledge intensity or prevalent market structure. Time fixed effects absorb global aggregate shocks such as geopolitical tensions occurring during the sample period. Their inclusion implies that identification of the drivers of AI adoption hinges on the residual variation across countries (or industries) within the same industry (or country) and year.[13]

For nation-wide policy variables (digital market regulation, labour market regulation, and innovation support), we assume their influence on AI adoption differs according to industry exposure. These variables are therefore interacted with an industry-specific exposure measure. For instance, digital market regulation is interacted with a country-invariant sectoral digital intensity index (Smiderle et al., 2026) and labour market regulation is interacted with US sectoral churn rates.[14] Similarly, innovation support is interacted with US sectoral R&D capital intensity.[15] The use of US data for sectoral interaction terms reduces reverse-causality concerns.

To account for some of the complexities shaping the influence of age on AI adoption, we also interact our industry-specific age distribution variables with some of the industry-specific (but country invariant) non-age-related factors that could affect this influence: a measure of job exposure to AI (Eloundou et al., 2024) and two measures of digital intensity (Smiderle et al., 2026; Calvino et al., 2018). Put differently, we assume that in each industry the influence of age on AI adoption is moderated by the propensity of tasks to be replaced or complemented by AI or by the diffusion of digital technologies.

3. Data, variable definitions and descriptives

Our analysis leverages 3 main data sources: (i) Eurostat's 'ICT Usage in Enterprises' database (ISOC), which includes a module reporting results of a firm-level survey of AI adoption in 157,000 enterprises with at least 10 employees and the self-employed for the years 2021, 2023,

12 Some bias might nonetheless persist as adoption rates in 2021-2025 partly incorporate adoption decisions taken in previous years. This is likely to be a minor problem due to limited adoption of the AI technologies covered by the analysis before 2020.

13 Results are robust to introducing also country*year and industry*year fixed effects (see Annex Tables C3).

14 Results do not change when replacing this interaction term by the industry exit rate or labour share (see Annex Tables C9).

15 Results do not change when replacing this interaction term by the industry intangible intensity or the share of organizational capital intensity (see Annex Tables C4).

2024, 2025;[16] (ii) EUKLEMS&INTANProd data (Bontadini et al., 2023), which has an extensive coverage of both National Accounts (NA) and non-NA intangible assets embedded in a consistent accounting framework; (iii) a variety of databases, including from the OECD, the IMF, the World Bank, Eurostat and academic research, to measure capabilities, incentives, government policies as well as demographics and other structural characteristics of industries (for details, see Table A3-A4 in the Annex).

Combining these sources, we end up with an unbalanced panel of 15 countries (Austria, Belgium, Germany, Denmark, Spain, Estonia, Finland, Greece, Italy, Lithuania, Latvia, Netherlands, Slovak Republic, Slovenia, Sweden) and 24 industries (for details, see Tables A1-A2 in the annex) covering 2021, 2023, 2024 and 2025.[17] This unbalanced panel contains 1,400 observations. Omitting obstacles from the analysis, the sample can be extended to 17 countries (with the addition of the Czech Republic and France that did not respond to the part of the survey concerning obstacles) totaling 1,592 observations.[18] Whenever possible, descriptive exhibits show the data available for the extended sample. We summarize below data sources, data construction and data properties grouping variables according to the taxonomy in Figure 1.

3.1 AI adoption

The AI module of Eurostat's 'ICT Usage in Enterprises' database (ISOC) provides the (NACE Rev. 2) sector-level shares of surveyed firms using seven AI technologies: autonomous robots, image recognition/processing, machine learning, natural language generation, process automation/decision support, speech recognition, and text mining (Table 1). It also provides these shares by the type of AI deployed, the purposes of use, and the mode of AI development (in-house, purchase, open source, or partnerships). An eighth technology was added in the 2025 survey, termed ‘Generative AI’.

[16] https://ec.europa.eu/eurostat/databrowser/explore/all/science?lang=fr&subtheme=isoc.isoc_e.isoc_eb&display=list&sort=category&extractionId=isoc_eb_ain2&node_code=isoc_eb_ain2

[17] The industries are (NACE Rev. 2): (C10–C12) Manufacture of food products; beverages and tobacco products; (C13–C15) Manufacture of textiles, wearing apparel, leather and related products; (C16–C18) Manufacture of wood, paper, printing and reproduction; (C19) Manufacture of coke and refined petroleum products; (C20) Manufacture of chemicals and chemical products; (C21) Manufacture of basic pharmaceutical products and pharmaceutical preparations; (C22–C23) Manufacture of rubber and plastic products and other non-metallic mineral products; (C24–C25) Manufacture of basic metals and fabricated metal products, except machinery and equipment; (C26) Manufacture of computer, electronic and optical products; (C27) Manufacture of electrical equipment; (C28) Manufacture of machinery and equipment n.e.c.; (C29–C30) Manufacture of motor vehicles, trailers, semi-trailers and other transport equipment; (C31–C33) Manufacture of furniture; jewellery, musical instruments, toys; repair and installation of machinery and equipment; (D) Electricity, gas, steam and air conditioning supply; (E) Water supply; sewerage, waste management and remediation activities; (F) Construction; (G) Wholesale and retail trade; repair; (H) Transportation and storage; (I) Accommodation and food service activities; (J58–J60) Publishing, audiovisual and broadcasting; (J61) Telecommunications; (J62–J63) IT and other information services; (M) Professional, scientific and technical activities; (N) Administrative and support service activities.

[18] Table C1 in Annex provides results of estimates without obstacle variables based on all the 17 countries. Results for non-obstacle variables are robust to this change of dataset composition.

Table 1. AI technologies surveyed by the Eurostat survey

Category	Content
Autonomous robots	AI technologies enabling the physical movement of machines through autonomous decisions based on observations of their surroundings
Image recognition and processing	AI technologies identifying objects or individuals based on images
Machine learning	Machine learning techniques (e.g. deep learning) used for data analysis
Natural language generation	AI technologies generating written or spoken language
Process automation and decision support	AI technologies automating workflows or assisting decision-making
Speech recognition	AI technologies converting spoken language into a machine-readable format
Text mining	AI technologies performing analysis of written language
Generative AI (added in 2025)	AI technologies that in response to a prompt or instructions create new content -- such as text, images, programming code, videos, or other data, based on available information and patterns it has learned from existing examples.

In this paper, we focus on three adoption outcomes: the share of surveyed companies using no AI, the 1st principal component of usage shares of each of the seven technologies for which a consistent time-series is available and the share of surveyed companies using at least three AI technologies. The first principal component of usage shares for each of the seven AI technologies is not the one-to-one complement of non-use of AI. In fact, this axis captures both the fact of using AI and the extent of AI use (henceforth “PC1 Adoption”).

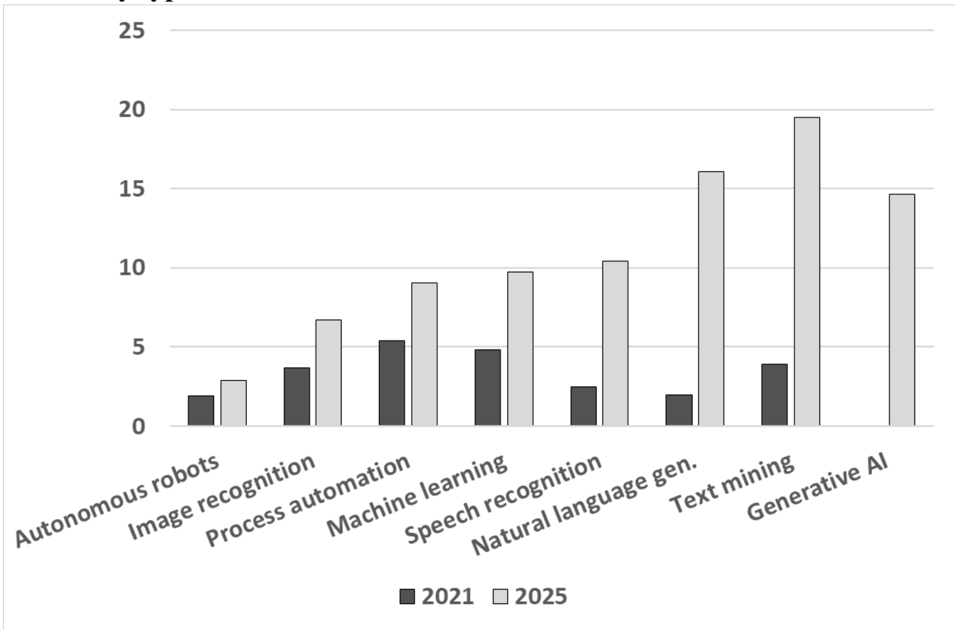
Figure 2 shows the evolution of adoption rates between 2021 and 2025, sorted by the size of the increase. AI adoption has boomed over this period, with growth particularly sharp in the most recent years (Panel A). Text mining and natural language generation have seen the largest gains, reaching approximately 20% of firms by 2025, roughly four times their 2021 levels. Adoption of generative AI, reported only since 2025, has reached around 15%. Machine learning and speech recognition have also grown substantially. The least widely adopted technology remains autonomous robots.[19] Adoption at the extensive margin (at least three AI technologies) rose five-fold from around 3% of firms in 2021 to approximately 15% in 2025, suggesting that firms also use AI for a rising variety of tasks (Panel B).[20]

[19] This partly reflects that robots are used mainly in two sectors: Manufacture of motor vehicles, trailers, semi-trailers and other transport equipment and Manufacture of coke and refined petroleum products.

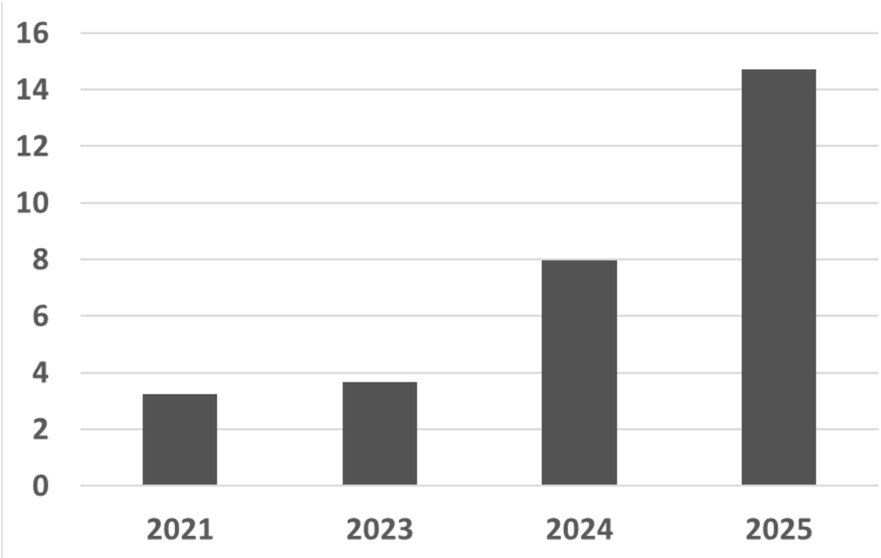
[19] The fact that an eighth AI was added in the 2025 survey contributes to the adoption increase that year. Since panel estimates are based on 7 technologies only, this has no influence on our results. Besides, cross-section results focusing on the year 2025 are insensitive to measuring adoption with the first component of the PCA on 7 or 8 AI technologies (see Annex Table C2).

Figure 2: Evolution of AI adoption between 2021 and 2025
% of firms - country*industry average

A. By type



B. At least three different technologies

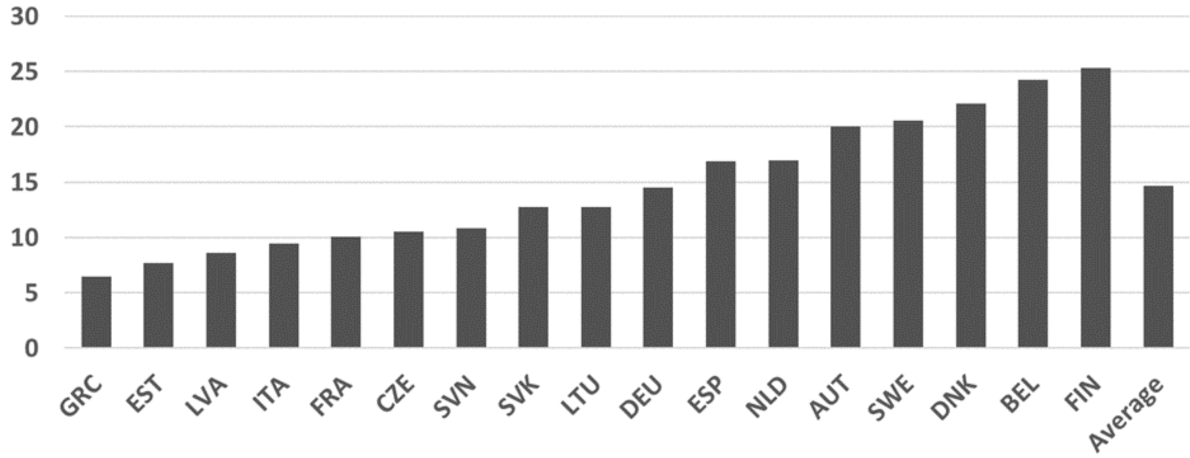


Note: Values are sorted by the difference between values in 2021 and 2025. Adoption of generative AI has been reported in the Eurostat Survey for the first time in 2025.
Source: Computed by the authors from the Eurostat survey on 'ICT usage and e-commerce in enterprises'.
Note: the increase of AI adoption is unchanged if we exclude France and the Czech Republic from the dataset (see Figure B1 in the Annex).

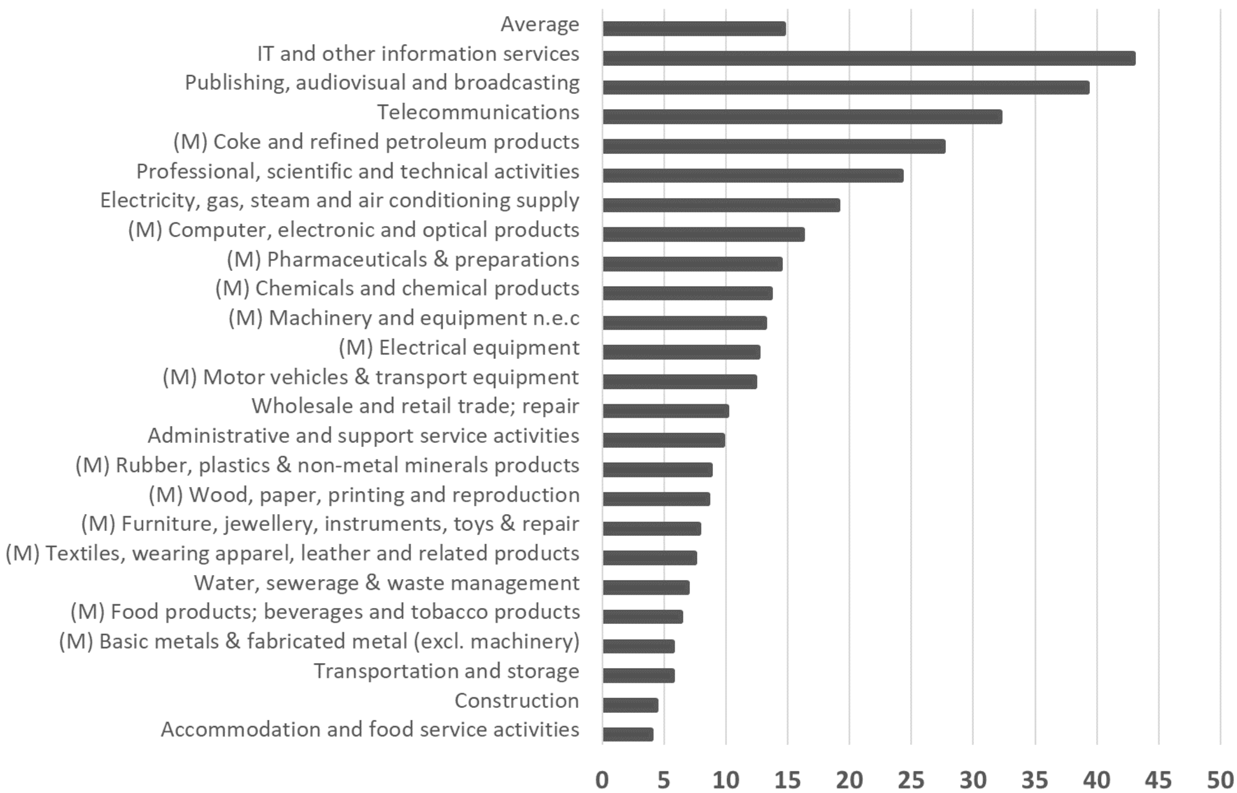
However, dispersion across countries and industries remains wide (Figure 3). In 2025, extensive adoption rates exceed 20% in Sweden, Belgium, Denmark, and Finland, while they remain below 10% in Estonia, Greece, Latvia, Italy, and France. Across industries, IT services (J62–J63), publishing and broadcasting (J58–J60), and telecommunications (J61) stand out with extensive adoption rates above 20–40%, while accommodation/food (I) and construction (F) remain at or below 5%. This hierarchy of AI adoption rates across industries is consistent with earlier findings (Eloundou et al. 2024; Bick et al. 2024; Calvino et al., 2025; Challapally et al., 2025).

Figure 3: Dispersion of extensive AI adoption across countries and industries
% of firms - at least three AI technologies, 2025 average

A. Across countries



B. Across industries



Note: Values are sorted by the share of enterprises using at least three AI technologies. The Czech republic and France are included.
Source: Computed by the authors from the Eurostat survey on 'ICT usage and e-commerce in enterprises'.

3.2 Drivers of AI adoption

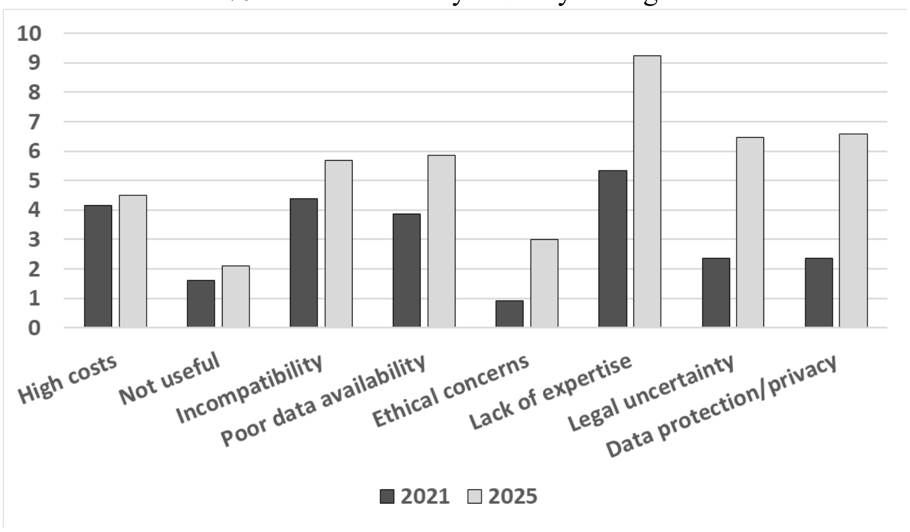
Perceived obstacles

From the Eurostat survey, we also draw data on eight reasons firms find it difficult to adopt AI. We group these into three categories: (i) Cost obstacles (one item: perceived excessive cost); (ii) Personal obstacles (three items: data protection/privacy concerns, ethical considerations, legal uncertainty); and (iii) Mismatch obstacles (four items: poor data availability, incompatibility with existing equipment, lack of relevant expertise, AI not useful for business). All these obstacles are expressed as the share of surveyed firms reporting each of them as relevant. Overall, the main perceived barriers are related to mismatch, with close to one fifth of firms not adopting AI for these reasons. The second main set of perceived barriers, quoted by close to 10% of firms, are personal obstacles. Cost concerns follow, with an average of 4 % of firms reporting that they do not use AI due to financial considerations.

Figure 4 shows how the perception of each obstacle has changed over time, sorted by magnitude of increase. All of them have increased in parallel with AI diffusion. Lack of expertise shows the largest increase. Personal concerns have grown substantially too, with legal uncertainty and concerns about security and privacy of data becoming the second-highest perceived obstacles to adoption in 2025. Cost concerns have apparently played a lesser role and have remained broadly stable. This may reflect the current experimentation stage of AI technologies, with providers' pricing strategies not yet set at break-even levels, thereby moderating perceived costs by users. Alternatively, the survey may suffer from an overlap between different kinds of perceived obstacles that may bias reported cost obstacles downwards: some of the personal or mismatch concerns might absorb part of the cost concerns because they are related to the costs that firms are forced to incur upon adopting AI (e.g. to meet litigation due to improper AI use or the necessary complementary investments in digital infrastructure or intangibles).

Figure 4: Evolution of perceived obstacles between 2021 and 2025

% of firms - country-industry averages



Note: Values are sorted by the difference between values in 2021 and 2025. Data for the Czech Republic and France are not available.
Source: Computed by the authors from the Eurostat survey on 'ICT usage and e-commerce in enterprises'.

Capabilities

Capabilities are captured by three indicators: organizational capital, ICT training and expertise, and digital access. *Organizational capital* intensity per hour worked mostly reflects investment in managerial skills (from the EUKLEMS & INTANProd database).[21] The two other indicators are constructed via PCA. *ICT training and expertise* aggregates information on the share of firms providing ICT training, employing ICT specialists, and doing both (all from the ISOC database) along with overall training capital intensity per hour worked (from the EUKLEMS & INTANProd database). *Digital access* combines the share of firms where at least 50% of employees have internet access, the share with access to high-speed broadband (≥1 Gb/s), and the share that owns a website (all from the ISOC database). We consider website ownership important in terms of access to data about commercial transactions that can be used by AI (e.g. for training or analytical purposes).

Incentives

Incentives are measured through four policy-related channels: (i) the impact of regulations in key non-manufacturing industries on the rest of the economy (henceforth 'regulatory burdens'), (ii) regulation of digital markets (henceforth 'DM'), (iii) the stringency of employment protection legislation (henceforth 'EPL') and (iv) innovation support via public R&D spending, subsidies or tax incentives. These indicators are shown in Annex B.

Regulatory burdens capture the trickle-down effects of anticompetitive regulations in a group of non-manufacturing industries that provide key intermediate inputs to the economy: energy (electricity and gas), transport (road, rail and air), communication (fixed and mobile), business services (legal, accounting, engineering and architecture) and retail trade. These effects (NMR^{up}) are computed as follows in each country c and industry i:[22]

$$NMR^{up}_{c,i,t} = \sum_j int^c_{i,j} \times NMR^t_{c,j} \;\; et \; int^c_{i,j} = 0 \; if \; i = j$$

Regulatory burdens depend on two components: (i) $NMR^t_{c,j}$, which captures the intensity of anticompetitive regulation in the non-manufacturing sector j in country c, and (ii) $int^c_{i,j}$ which represents the ratio of intermediate inputs sourced from sector j to the output of downstream sector i. These components are measured using the OECD sectoral Product Market Regulation (PMR) indicators and input-output tables, respectively.[23] The sectoral PMR cover a range of regulations governing entry, access to grids, licensing and business behavior in the non-manufacturing sectors. To avoid possible endogeneity biases, in the empirical analysis we

[21] EUKLEMS data are chained linked volumes 2015 in millions of national currency, which we convert in 2015 PPPs.

[22] This approach has been developed by Conway and Nicoletti (2006), Barone and Cingano (2011) and Bourlès et al. (2013).

[23] The OECD indicators are available at https://www.oecd.org/en/topics/product-market-regulation.html and their cross-country pattern is presented in figure B3 in the annex.

source *int* from the 2015 input-output table of the United States and use the 2018 PMR data to measure *NMR*.[24]

Digital market regulation captures public interventions explicitly aimed at influencing competitive pressures in digital markets via antitrust investigations, merger control or ex ante regulations (in the areas of fair trade, contestability and access to data). We rely on the corresponding nation-wide OECD PMR indicator, which we interact with Smiderle et al. (2026)'s digital intensity indicator in the United States, which captures the degree of workforce digitalization within each sector.[25] We limit possible endogeneity issues by measuring both regulation and digital intensity in 2018.[26]

Employment protection legislation constrains to varying degrees the ability of firms to implement the workforce adjustments potentially required by AI adoption. We measure it relying on the OECD nation-wide EPL index, which we interact with US sectoral churn rates in 2018 assuming that sectors with structurally higher job turnover are more exposed to such constraints. The EPL index covers hiring and firing procedures for workers with temporary and permanent contracts as well as obligations in case of collective dismissals (see OECD, 2020).

Innovation support aggregates information about seven nation-wide R&D expenditure, subsidies and tax incentive items which we interact with 2018 US sectoral R&D capital intensity. The underlying assumption is that sectors with structurally higher R&D intensity are better able to benefit from innovation support policies, as they are characterized by a stronger accumulation of knowledge-based capital and innovation-related assets. The seven indicators can be grouped into two categories: (i) a set of indicators related to total and public-financed R&D expenditures and (ii) a set measuring several fiscal incentives for R&D. Spending indicators include shares (in GDP) of total R&D spending (from World Bank's *World Development Indicators* database),[27] of R&D spending carried out by firms but financed by the government through direct grants or indirectly (e.g. public contracts) and of R&D spending performed by the higher education sector (from OECD *Main Science and Technology Indicators)*. Incentive indicators include implicit R&D tax support rates, measured for four categories of firms: large enterprises and SMEs, either profitable or loss-making (from the OECD *R&D Tax Incentives* database).

[24] The United States is not covered by Eurostat's AI survey and has been among the least regulated economies for decades. Therefore, it is unlikely that intermediate input intensities and regulation are related in ways that could bias our measure of regulatory burdens.

[25] To measure the degree of workforce digitalization, each occupation is assigned a digital skill intensity score, calculated as the proportion of digital skills in the total set of competencies required to perform that occupation, following the methodology developed by Lennon et al. (2023). These occupational-level scores are then aggregated to the industry level, using employment shares from labour force survey data as weights.

[25] Results are unchanged if we use the average 2018-2023 instead of the 2018 value of this variable, see Table C5 in Annex.

[27] This measures gross domestic R&D expenditures (GERD) as a percentage of GDP, encompassing capital and current expenditures across the four main performing sectors: business, government, higher education, and private non-profit organizations. This indicator covers basic research, applied research, and experimental development.

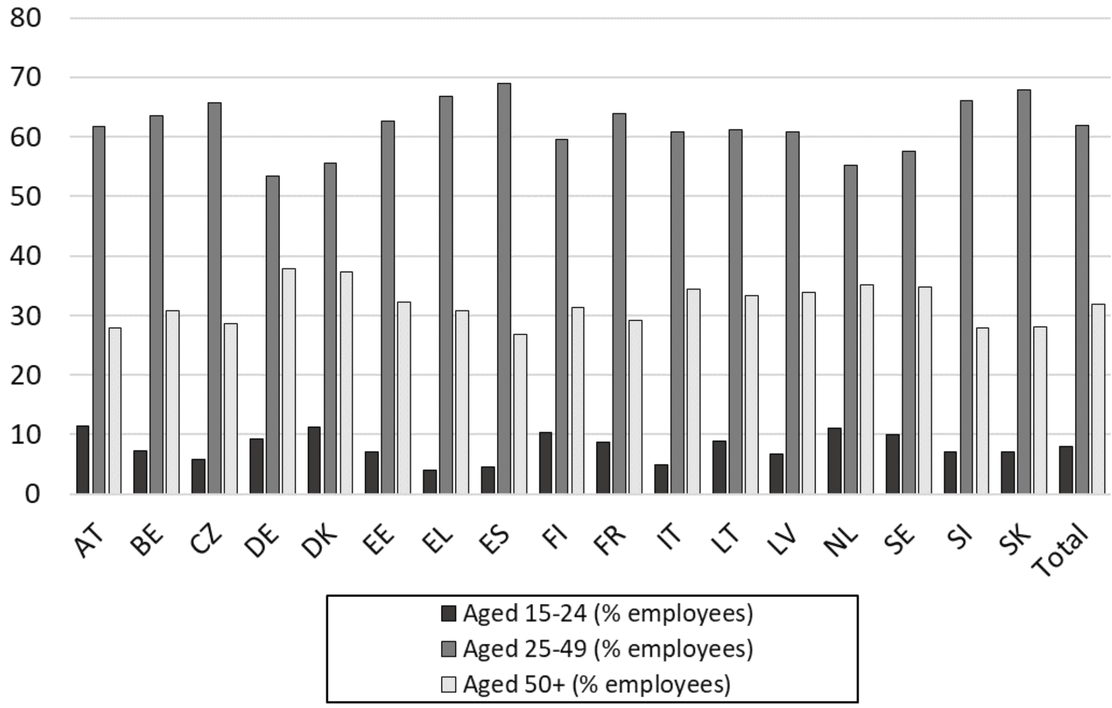
Demography

Demographic variables are drawn from Eurostat's *Labour Force Survey* for 2019, prior to the AI adoption surge. We use sectoral shares of workers aged 15–24, 25–49 and 50+ to map the age distribution of the workforce into young, prime-age and senior workers. We also interact these with the Eloundou et al. (2024) AI exposure indicator (E1: potential for ≥50% improvement in task execution through AI) to account for the possible moderating effect of exposure on adoption propensities across age.

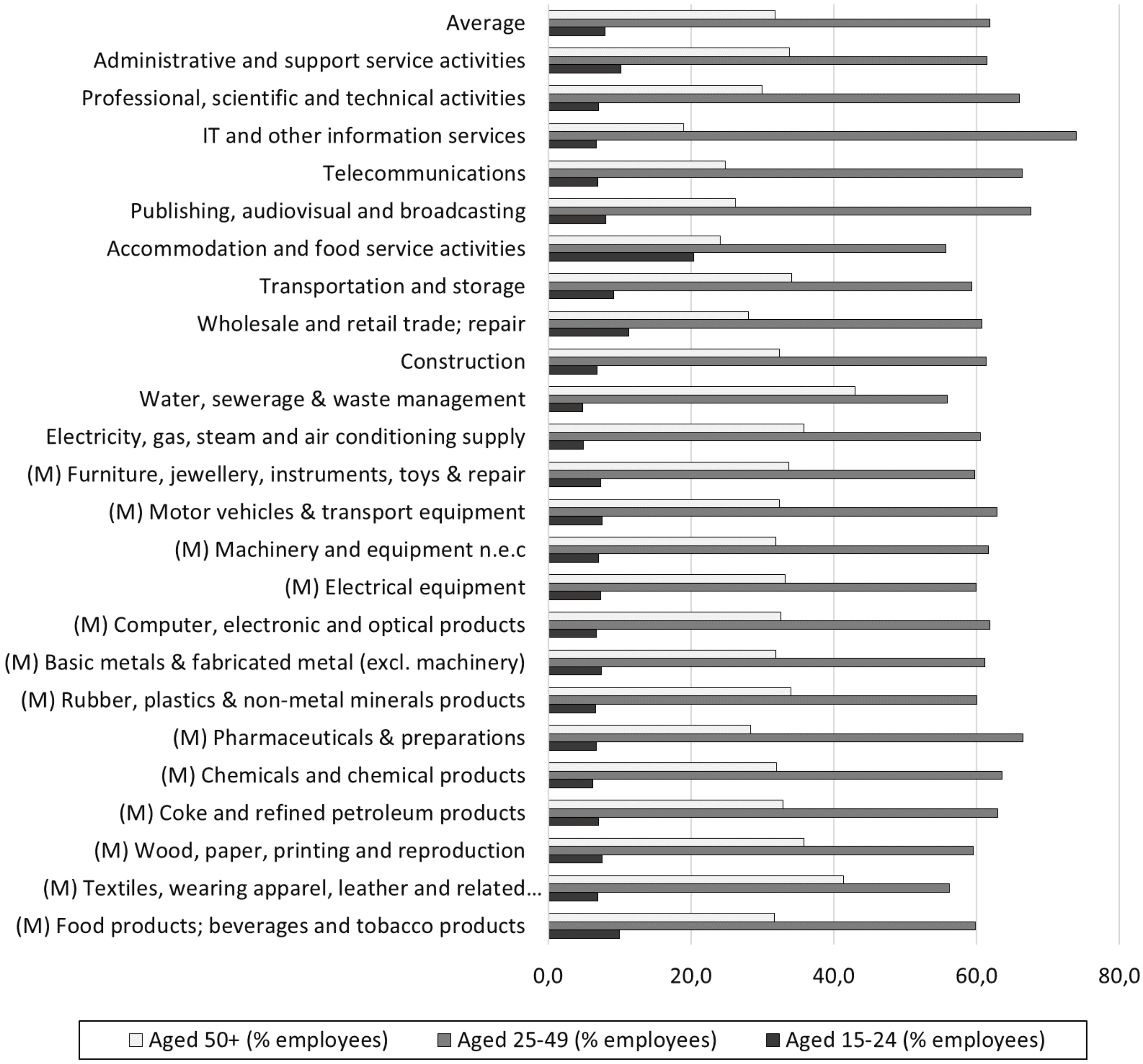
Figure 5 displays the average share of workers in each age group across countries (Panel A) and industries (Panel B). Across both dimensions, a similar pattern emerges. Most employees (approximately 60% on average) belong to the 25–49 age group. Senior workers aged 50 and over represent roughly 30% of the employed population, while young workers aged 15–24 account for only about 10%. Still there is significant heterogeneity across both countries and industries. At country level, this likely reflects not only differences in population ageing but also differences in retirement age and schooling systems. As for industries, accommodation and food services (I), retail trade (G) and administrative and support services (N) unsurprisingly employ the largest shares of young workers (around 20%, 11% and 10%, respectively), compared to an average of 7% elsewhere, likely reflecting their relatively low skill requirements at entry level. The presence of mature workers is particularly strong in the information and communication services (J) for opposite reasons.

Figure 5: Age distribution of the workforce (%) in 2019

***Panel A*. Across countries**



Panel B. **Across industries**



Source: Computed by the authors from Eurostat's LFS.

4. RESULTS

We first present the results of the principal component analyses (PCA), then organize the regression findings across three subsections: main results, obstacles to adoption, and the effects of workforce age. Additional results and robustness analyses are provided in the Annex.

4.1 Principal component analysis

PCAs were performed to summarize (i) adoption of the seven AI technologies reported in the Eurostat survey, (ii) the eight perceived obstacles to adoption, (iii) the four indicators of ICT training and expertise, (iv) the three indicators of digital access and (v) the seven indicators of innovation support.[28,29] Table 2 describes the main results. In most cases, the first principal component explains over 60% of total variance — our threshold for retaining a single axis. AI adoption and innovation support see particularly high first-component variance shares (72% and 74% respectively), while the obstacles PCA shows a lower share (61%), consistent with the different nature of cost, personal, and mismatch concerns. When PCAs are run separately for personal obstacles and mismatch obstacles, the first components explain 81% and 67% of variance, respectively.

Table 2. Summarizing adoption and its drivers via principal component analysis

PCA variables used in regressions	# vars	Individual elements in PCA	% variance explained		
			1st comp.	2nd comp.	3rd comp.
AI adoption (PC1)	7	Autonomous robots; Image recognition/processing; Machine learning; Natural language generation; Process automation/decision support; Speech recognition; Text mining	72	11	6
Obstacles	8	Data protection/security concerns; Ethical concerns; Legal uncertainties; Too costly; No availability of appropriate data; Incompatibility with existing equipment; Lack of relevant expertise; Not useful for business	61	11	9
Personal obstacles	3	Data protection/security concerns; Ethical concerns; Legal uncertainties	81	15	4
Mismatch obstacles	4	No availability of appropriate data; Incompatibility with existing equipment; Lack of relevant expertise; Not useful for business	67	20	9
ICT training/specialist	4	ICT training of workers; ICT specialists hired; ICT training & ICT specialists; Training intensity	73	22	3
Digital access	3	At least 50% of staff with access to internet; Company has website; High-speed internet (≥1 Gb/s)	65	22	13
Innovation support	7	Business R&D spending financed by government; Higher education R&D spending; Total R&D expenditure; R&D tax incentives: profitable large firms; loss-making large firms; profitable SMEs; loss-making SMEs	74	22	2

Note: Details of PCA results are provided in the Annex.
Sources: Authors' estimates

4.2 Main results

Table 3 reports the main regression results for three adoption outcomes: no AI adoption (column 1), the first principal component of the individual AI adoption rates (PC1 AI adoption, column 2), and extensive adoption of at least three AI technologies (column 3). We interpret column 2

28 PCAs are useful because the correlations between the individual variables within these different groups are sometimes very high (annex B10-a-b-c).

29 As the indicators of innovation support are nation-wide, we performed the PCA on the interaction of these indicators with industry-specific R&D capital intensity in the US as explained in the previous section.

as the influence of adoption drivers on adoption of *any* AI technology, independent of their range: PC1 AI adoption corresponds to both to the AI adoption and the extent of the AI adoption. Results are presented using the first PCA axis of all obstacles combined to keep the table compact; disaggregated results by obstacle type are presented in Section 4.3. Also, we use the share of prime-age workers (25–49) as the main age variable in Table 3. Section 4.4 provides a full analysis of the age–AI nexus including the shares of all three age groups and their interaction with AI industry exposure.[30]

We split Table 3 in two panels: Panel A reports results for the 2021-2025 period (1400 observations) and the PC1 AI adoption outcome includes seven technologies, Panel B reports results for a cross-section focusing on 2025 only (350 observations) and the PC1 AI adoption outcome includes eight technologies. This is because, as already mentioned, Eurostat has added in 2025 an eighth technology (Generative AI) in the Survey. This introduces a slight inconsistency in the time-series of extensive adoption rates (and potentially also in the non-adoption and obstacle ones) as earlier adopters of generative AI may have been excluded from the sample.[31] Moreover, as shown in Figure 2, adoption has progressed very rapidly in the last available year. Therefore, a specific focus on 2025 is warranted for both robustness and economic reasons, even though a direct comparison with panel results is difficult due to the lesser number of observations.

All regressions include country, industry and year fixed effects and standard errors are robust, clustered at the country*industry level to account for within-group correlation across years. All variables are standardized to allow direct comparison of coefficients.

In these baseline regressions, the perceived obstacle composite (PC1 of all obstacles) is contemporaneous while all other drivers are pre-determined at pre-sample levels to reduce reverse-causality concerns. Hence, for pre-determined variables, the identifying variation in these baseline regressions is driven mainly by cross-sectional differences across the 350 country-industry cells. Additional regressions, with instrumented obstacles (using a Bartik approach), other drivers lagged and time-varying, and crossed fixed effects (country*year and industry*year) are reported in the Annex. Results shown in Table 3 are robust to these changes in specification.

[30] In all regressions, dropping age variables has no impact on the estimated coefficients of the other variables.

[31] As the 'non-adoption' and 'at least three technologies' shares are provided directly by Eurostat, it is not possible to ensure full consistency between their 2025 and earlier values. Conversely, the PC1 Adoption variable (which is based on individual adoption rates) can be computed consistently over the period by focusing on only seven technologies. However, results using the PC1 constructed with seven technologies and those using the PC1 including eight technologies are very similar when focusing only on 2025, suggesting that the inclusion of the eighth technology does not materially affect the measurement of AI adoption in that year. Results are presented in Table C2 in the Annex.

Table 3: Main results

Panel A. Panel regressions (2021-2025)

VARIABLES	No AI adoption (1)	PC1 AI adoption (2)	Extensive AI adoption (3)
Obstacle_{cit} (PC1)	0.118***	-0.120***	-0.135***
	(0.026)	(0.036)	(0.029)
$\text{Organisational capital}_{ci0}$	-0.075***	0.188***	0.180***
	(0.025)	(0.035)	(0.040)
$\text{ICT training \& expertise}_{ci0}$ (PC1)	-0.268***	0.216***	0.195***
	(0.079)	(0.070)	(0.063)
$\text{Digital access}_{ci0}$ (PC1)	-0.006	0.052	0.047
	(0.074)	(0.070)	(0.061)
$\text{Innovation support}_{ci0}$(PC1)	0.005	0.094	0.102*
	(0.038)	(0.075)	(0.058)
$\text{Regulatory burden}_{ci0}$	0.015	-0.104**	-0.083*
	(0.047)	(0.050)	(0.049)
DM * $\text{digital intensity}_{ci0}$	1.245***	-0.741*	-0.788*
	(0.329)	(0.390)	(0.403)
EPL_c* churn_{ci0}	0.222	-0.492***	-0.541***
	(0.172)	(0.170)	(0.170)
$\text{Share age 25-49}_{ci0}$	-0.071**	0.102*	0.095**
	(0.034)	(0.052)	(0.040)
Constant	2.139***	-1.548***	-1.657***
	(0.440)	(0.469)	(0.473)
Observations	1,400	1,400	1,400
R-squared	0.711	0.629	0.616
Country FE	yes	yes	yes
Industry FE	yes	yes	yes
Year FE	yes	yes	yes

Panel B. Cross section (2025)

VARIABLES	No AI adoption (1)	PC1 AI adoption (2)	Extensive AI adoption (3)
Obstacle_{cit} (PC1)	0.071**	-0.091*	-0.152***
	(0.035)	(0.049)	(0.056)
$\text{Organisational capital}_{ci0}$	-0.213***	0.276***	0.466***
	(0.053)	(0.058)	(0.094)
$\text{ICT training \& expertise}_{ci0}$ (PC1)	-0.219**	0.120	0.239*
	(0.108)	(0.098)	(0.143)
$\text{Digital access}_{ci0}$ (PC1)	0.146	-0.088	-0.141
	(0.143)	(0.112)	(0.151)
$\text{Innovation support}_{ci0}$(PC1)	0.092	0.116	0.123
	(0.073)	(0.137)	(0.122)
$\text{Regulatory burden}_{ci0}$	-0.009	-0.091	-0.112
	(0.080)	(0.080)	(0.114)
DM * $\text{digital intensity}_{ci0}$	1.990***	-1.332**	-2.758***
	(0.502)	(0.542)	(0.912)
EPL_c* churn_{ci0}	0.308	-0.602**	-0.700*
	(0.269)	(0.269)	(0.358)
$\text{Share age 25-49}_{ci0}$	-0.090	0.179*	0.225**
	(0.061)	(0.096)	(0.091)
Constant	2.143***	-2.049***	-2.918***
	(0.671)	(0.645)	(1.068)
Observations	350	350	350
R-squared	0.812	0.717	0.784
Country FE	yes	yes	yes
Industry FE	yes	yes	yes
Year FE	-	-	-

*Robust standard errors in parentheses (clustered at country×industry). *** p<0.01, ** p<0.05, * p<0.1. All specifications include country, industry, and year fixed effects. Variables standardized.*

Notes: (PC1) indicates that the variable is summarized by the 1st factorial axis of the PCA (see Table 2). "No AI adoption" and "At least three AI technologies" shares are directly provided by Eurostat. The sample covers the 15 countries for which data on obstacles are available.

Overall, the results are consistent across the three AI adoption measures. Taking results in Panel A causally, *perceived obstacles* (the combined PC1) significantly reduce adoption: a one-standard-deviation rise in the obstacle composite increases the share of non-adopters by roughly 12% of a standard deviation and reduces both PC1 adoption and intensive adoption by comparable magnitudes. Thus, a unit reduction in the (composite) share of perceived obstacles curbs the share of non-adopters by 2 percentage points and raises the shares of extensive AI adopters by 1.5 percentage points.[32]

ICT training & expertise and organizational capital are the two most important *capability drivers* of adoption. A one-standard-deviation rise in organizational capital is associated with a reduction of 7.5% of a standard deviation for non-adopters and an increase of roughly 18–19% of a standard deviation for extensive adopters. The ICT training and expertise composite shows even larger effects, with coefficients exceeding those of organizational capital in absolute value across all three columns but especially for non-adopters. The corresponding effects of a unit increase in organizational capital intensity (or the ICT training and expertise composite) are 1.3 percentage points (3.3 pp) for non-adopters and 0,8 percentage points (2.1 pp) for extensive adopters. This points to the critical role played by complementary skills for enabling digital or AI adoption (Nicoletti et al., 2020; Bick et al., 2026). Digital access, while correctly signed, does not reach conventional significance levels.

Among the *incentive drivers*, employment protection legislation interacted with sectoral churn rates shows the strongest effect on adoption outcomes, suggesting that strict hiring and firing rules raise the adjustment costs of technology adoption, with the effect rising with sectoral job turnover. Upstream regulatory burdens are also negatively associated with adoption: anticompetitive regulations lead to rent capture by regulated upstream sectors, discouraging downstream firms from mobilizing AI.[33] Innovation support is positive and marginally significant for intensive adoption, consistent with R&D incentives having a stronger impact on the breadth of AI use than on initial take-up. Finally, digital market regulation interacted with sectoral digital intensity has a large, positive and highly significant coefficient on non-adoption and a negative, marginally significant coefficient on both adoption outcomes, suggesting that public interference with digital market mechanisms ought to be cautious. However, given the relatively low cross-country variability of the OECD digital regulation indicator in 2018 these results should only be considered indicative.[34]

As for *demography*, the prime-age worker share (25–49) impacts positively and significantly on adoption and negatively and significantly on non-adoption. In other words, a one percentage point increase in this share tends to increase the extensive AI adoption share by roughly the same amount according to our estimates. Additional regressions reported in the Annex (Table C10), which interact the age variable with a country-invariant measure of sectoral

32 Annex Table B7 reports the standard deviations of all variables.

33 This echoes previous analyses showing a negative impact of product and labour market regulations on ICT adoption (Cette and Lopez, 2012; Cette et al., 2018) and digital technologies (Nicoletti et al., 2020).

34 The low variability of the indicator makes results sensitive to outliers. Nonetheless results are robust to using the 2018-2023 average of the regulation indicator, which shows more variability and less sensitivity.

organizational capital intensity, suggest that the positive effect of the share of prime-age workers rises with such intensity. One interpretation is that the presence of skilled management capable of implementing the organizational changes needed to accommodate AI adoption is key for reaping the adoption advantage provided by a higher share of more experienced workers.

Cross-section results for 2025 are broadly similar for most variables, with some important exceptions. First, the positive impact of organizational capital on adoption becomes much stronger. Second, while regulatory burdens lose significance, the negative impact of EPL in high churn sectors is boosted. Finally, the impact of a higher share of prime-age workers also rises relative to panel estimates. It is reassuring that restricting the sample to the most recent period, when adoption rose fastest, confirms most of the panel results. But it is difficult to gauge whether the changes in results for some of the adoption drivers are a statistical artifact due to the lesser number of observations or an evolution over time of the link between drivers and adoption outcomes.

These results are robust in several important respects. First, adding control variables — firm size, trade openness, ICT capital intensity, and levels of trust (as recorded in the European Social Survey) interacted with US organizational capital intensity leaves all main coefficients unchanged in sign and significance. Although controls display the expected sign, most are individually insignificant, and so they are not included in the main tables (see Annex Table C7).[35] Second, the EPL and innovation support results are robust to using alternative exposure measures, as US job exit rates or the labour-share-in-output ratio for EPL and the US organizational capital or intangible intensity per hour worked for innovation support, in place of churn rates and R&D capital intensity per hour worked (Annex Table C4). Third, adding crossed country*year and industry*year fixed effects alongside the main fixed effects leaves all coefficients stable in sign and close in magnitude, with only minor losses in precision (Annex Table C3). Fourth, results are also robust to incorporating temporal variation in all explanatory variables, using lagged values to preserve pre-determination (Annex Tables C8). Fifth, results are also robust to instrumenting obstacles via a Bartik-type instrument (average obstacle perceptions, dropping the country for which adoption is measured) (Annex Table C6). Finally, results are robust to dropping countries or industries from the sample one by one (Annex Tables C12a-b-c).

4.3 A closer look at the role of perceived obstacles

To understand which types of obstacles matter most, and how their role has evolved over time, Table 4 reports regressions decomposing obstacles for the extensive adoption outcome. Columns (1)–(3) use the full panel (2021–2025); columns (4)–(5) use cross-sections for 2025

[35] Surprisingly, firm size is particularly insensitive: even when obstacles or all explanatory variables are removed, it remains insignificant. It becomes significant only when country or industry fixed effects are dropped (Annex Table C11), suggesting that size effects are absorbed by structural heterogeneity captured by the fixed effects.

and the average 2021–2024, respectively. All regressions include also estimates for the other drivers, which remain unchanged and we do not report for brevity.

Table 4. Obstacle decomposition

(dependent variable: extensive AI adoption)

	Panel 2025-2021			Cross section Year 2025	Cross section Average 2024-2021
VARIABLES	(1)	(2)	(3)	(4)	(5)
Cost obstacle$_{cit}$	-0.011	-0.010	-0.011	0.015	-0.111**
	(0.028)	(0.031)	(0.025)	(0.064)	(0.050)
Personal obstacle$_{cit}$(PC1)	-0.014		-0.003	0.072	-0.160***
	(0.036)		(0.035)	(0.089)	(0.057)
Mismatch obstacle$_{cit}$(PC1)	-0.122***	-0.121***		-0.271***	0.028
	(0.039)	(0.040)		(0.101)	(0.074)
Ethical concerns$_{cit}$		0.007			
(E_AI_BEC)		(0.034)			
Poor data protection$_{cit}$		0.003			
(E_AI_BCDP)		(0.033)			
Legal uncertainty$_{cit}$		-0.025			
(E_AI_BLEG)		(0.047)			
Incompatibility$_{cit}$			-0.063		
(E_AI_BINC)			(0.043)		
Not useful$_{cit}$			-0.001		
(E_AI_BNU)			(0.029)		
Lack of expertise$_{cit}$			-0.071		
(E_AI_BLE)			(0.048)		
Poor data availability$_{cit}$			-0.016		
(E_AI_BDDT)			(0.039)		
Constant	-1.593***	-1.601***	-1.542***	-3.138***	-0.255
	(0.486)	(0.489)	(0.482)	(1.028)	(1.049)
Observations	1,400	1,400	1,400	350	350
R-squared	0.617	0.617	0.618	0.788	0.682
Country FE	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	-	-

*Robust standard errors in parentheses (clustered at country×industry). *** p<0.01, ** p<0.05, * p<0.1. All specifications include the full set of controls. Year fixed effects included in columns (1)–(3).*
Notes: Eurostat's acronyms of the various types of perceived obstacles in parentheses. The sample includes the 15 countries for which data on obstacles are available.

Several results stand out. First, multicollinearity among the different obstacle sub-types is high: no effect of the obstacles can be identified when they are included individually in the regression (columns 2 and 3). Yet, they are all correctly signed and significant when they are included one by one in the regression (see Annex Table C14-a-b). This motivates our PCA aggregation approach.

Second, when the mismatch and personal obstacles PCA axes are included jointly (column 1), the mismatch PC1 dominates strongly and this result remains unchanged if the personal obstacle group is replaced by its three individual components (column 2). This tends to exclude that its effect is an artefact of multicollinearity with personal concerns. Conversely, where the mismatch group is replaced by its individual components, the personal obstacle group remains insignificant (column 3). Obstacles related to the direct costs of AI adoption remain correctly signed but insignificant throughout. Therefore, panel estimates suggest that the overarching obstacle for AI adoption has been the failure to match the new technology with adequate skills, complementary digital tools, appropriate data or new business models.[36]

Third, and most importantly, the cross-section regressions suggest that mismatches may have acquired this dominant role only recently. In the 2025 cross-section (column 4), mismatch obstacles are highly significant while other concerns are not. In the 2021–2024 average (column 5), mismatch concerns lose significance while personal concerns dominate. This temporal pattern is consistent with a natural progression in the adoption cycle: during the early diffusion phase (2021–2024), firms were held back primarily by costs, legal uncertainty, ethical concerns, and data protection worries about a novel technology. As adoption broadened after 2024 the binding constraint shifted to whether firms have the expertise, data, and compatible systems to make productive use of AI. Estimates of obstacles related to the direct costs also show a reversal over time perhaps reflecting the below-cost pricing strategies of the main generative AI providers, aimed at gaining market shares over competitors during the rapid diffusion phase of the technology.

Another factor that may impinge on the results concerning cost obstacles is their close link with the other groups of perceived obstacles. Specifically, cost-related obstacles are likely to be closely linked to mismatch obstacles (and, to a lesser extent, personal obstacles). The corresponding item in the Eurostat survey is: "Enterprises do not use AI technologies because the costs seem too high." However, the notion of "costs" can cover several dimensions. It can refer to the direct cost of acquiring AI technologies (e.g., the price of software), but also to other kinds of direct or indirect costs, especially at the initial stage of AI diffusion. On the mismatch side, these can include, for instance, expenses related to adapting or updating algorithms, workforce training costs, or organizational costs associated with adapting internal company processes. These indirect costs could be dissuasive given that the potential company-wide benefits of AI remain uncertain.

4.4. Workers' age and AI adoption

Table 5 explores in detail how the age distribution of the workforce is associated with AI adoption, including the moderating effect of AI exposure at the industry level. Odd-numbered columns report results using separate shares for young (15–24) and senior (50+) workers; even-numbered columns include interaction terms with AI exposure.

[36] Additional results also show that poor data protection seems to have a detrimental impact only on extensive adoption. Other obstacles have a detrimental impact on our three measurements of AI adoption. (Annex Table C14-a-b).

Table 5. Workers' age and AI adoption

VARIABLES	No AI adoption (1)	No AI adoption (2)	No AI adoption (3)	No AI adoption (4)	PC1 AI adoption (5)	PC1 AI adoption (6)	PC1 AI adoption (7)	PC1 AI adoption (8)	Extensive adoption (9)	Extensive adoption (10)	Extensive adoption (11)	Extensive adoption (12)
Share age 15-24$_{ci0}$	0.069**	0.214***			-0.064**	-0.217***			-0.066**	-0.223***		
	(0.029)	(0.061)			(0.029)	(0.064)			(0.027)	(0.059)		
Share age 50+$_{ci0}$	0.026	0.118**			-0.061	-0.206**			-0.054*	-0.188***		
	(0.031)	(0.054)			(0.048)	(0.089)			(0.033)	(0.061)		
Share age 15-24$_{ci0}$*Eloundou		-0.179***				0.191***				0.196***		
		(0.062)				(0.066)				(0.064)		
Share age 50+$_{ci0}$*Eloundou		-0.134**				0.208**				0.194***		
		(0.067)				(0.081)				(0.067)		
Share age 25-49$_{ci0}$			-0.071**	-0.152***			0.102*	0.243**			0.095**	0.229***
			(0.034)	(0.058)			(0.052)	(0.094)			(0.040)	(0.071)
Share age 25-49$_{ci0}$ *Eloundou				0.346*				-0.598**				-0.565***
				(0.201)				(0.241)				(0.209)
Constant	2.048***	1.501***	2.139***	2.100***	-1.515***	-0.826	-1.548***	-1.482***	-1.611***	-0.937*	-1.657***	-1.594***
	(0.429)	(0.447)	(0.440)	(0.442)	(0.483)	(0.515)	(0.469)	(0.478)	(0.479)	(0.508)	(0.473)	(0.472)
Observations	1,400	1,400	1,400	1,400	1,400	1,400	1,400	1,400	1,400	1,400	1,400	1,400
R-squared	0.711	0.713	0.711	0.712	0.627	0.631	0.629	0.631	0.614	0.618	0.616	0.618
Country FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

*Robust standard errors in parentheses (clustered at country×industry). *** p<0.01, ** p<0.05, * p<0.1.*
All specifications include the full set of drivers.

Given the wide heterogeneity in sectoral exposure to AI (Eloundou et al., 2024; André & Schief, 2026), it is reasonable to assume that the age-adoption nexus is moderated by exposure. This is because industry age interacts with other factors to influence AI adoption. These include workers' experience, workers' skills and the propensity of workers' tasks to be replaced or complemented by AI systems. For instance, more exposed sectors (such as information services) structurally employ a more skilled and digitally literate workforce than other sectors at all ages. Hence one would expect a lesser influence of age on adoption rates the more exposure to AI rises.

Accordingly, in Table 5 we show results interacting the age variables with the Eloundou et al. (2024) sectoral exposure measures.[37] Exposure varies greatly between industries: the proportion of jobs exposed ranges from less than 8% in the construction (industry F) to more than 35% in IT and other information services (J62-J63) (Annex Figure B9). The Annex also reports sensitivity to three alternative country-invariant sectoral exposure variables measuring digital intensity (Annex Tables C15-a-b-c).

Columns (1), (3), (5), (7), (9), and (11) confirm a clear inverted U-curve between age and adoption. Higher shares of young workers (15–24) are positively associated with non-adoption and negatively associated with both PC1 and intensive adoption. Prime-age workers (25–49) display the opposite pattern across all three adoption outcomes. Senior workers (50+) are

[37] Eloundou et al. (2024) classify tasks in each occupation according to different levels of AI exposure then aggregate occupations in each industry to derive industry exposure levels. Here we use their exposure level E1, corresponding to a 50% improvement in task execution through AI. Their reference years are 2020-2022. Our results are robust to the other exposure measures proposed by Eloundou et al. (2024).

similarly signed to young workers but the effects are smaller and only significant at conventional levels for extensive AI adoption.

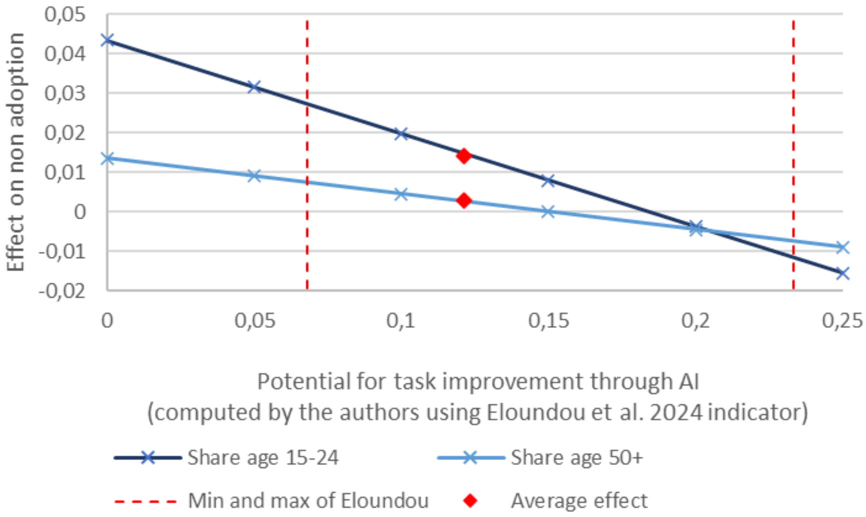
The interaction terms with AI exposure (even-numbered columns) reveal that the inverted U-curve flattens substantially as industry AI exposure rises. The implication is that in industries at the high end of the AI exposure distribution, the negative association between high youth shares and adoption essentially disappears. For senior workers, the flattening is also significant in the same direction, though the interaction for seniors is less robust across alternative exposure indicators (Annex Tables C15-b-c): when using the Smiderle et al. (2026) digital intensity indicator or the Calvino et al. (2018) sector digitization taxonomy in place of the Eloundou indicator, the senior worker interaction is weaker or loses significance, while the young-worker interaction remains robust. This suggests that the exposure-moderation effect is cleaner for youth than for seniors.

Figure 6 shows the flattening of the inverted U-curve graphically by plotting the total marginal effects as a function of the Eloundou indicator for non-adoption (Panel A), PC1 adoption (Panel B), and extensive adoption (Panel C) respectively, separately for young (15–24) and senior (50+) workers. At the sample-mean AI exposure level (Eloundou index ≈ 0.12), the average effect of young workers on non-adoption recovers to 0.013 (0.069/4.01), which corresponds precisely to the point on the blue line in Figure 6 at mean exposure, confirming the internal consistency of the standardized regression results.[38]

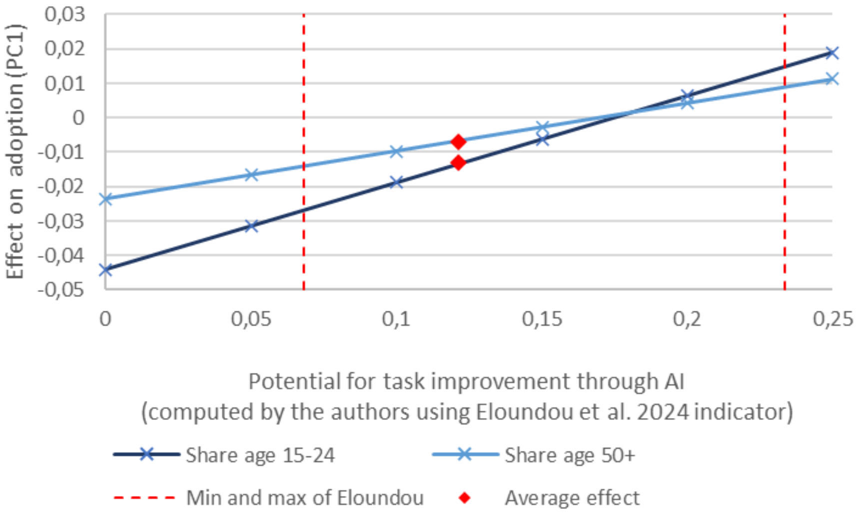
[38] Because the variables are standardised in the regressions, the total marginal effect of, say, the young-worker share (X) on adoption, given AI exposure level Z, is correctly computed as: $\partial Y/\partial X = (b_1/\sigma_X) + (b_2 \cdot Z/\sigma_{XZ})$, where σ_X and σXZ are the standard deviations of X and the interaction term respectively. This corrects for the fact that simply computing ($b_1 + b_2 \cdot Z$) conflates the standardisation of the constituent variable and its interaction.

Figure 6. Marginal effects of age on adoption outcomes vs sectoral AI exposure

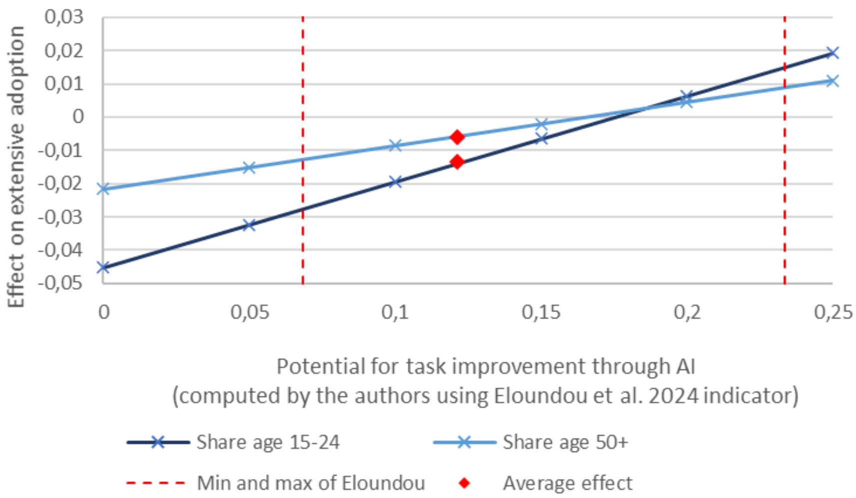
Panel A: Non adoption



Panel B: PC1 adoption



Panel C: Extensive adoption



A natural concern is whether the young-worker effect reflects genuine age dynamics or is instead a proxy for job precariousness, since sectors with high youth employment (accommodation, retail) tend to have both high turnover and relatively low AI exposure. To investigate this, the sample was split according to industry-level job turnover and job exit rates (Annex Tables C16-a-b). While the inverted U-curve holds for the high-turnover subsample and loses significance for the low-turnover subsample, splitting by turnover essentially produces two groups corresponding to manufacturing versus service sectors rather than genuinely 'precarious' versus 'stable' employment sectors. For instance, the communication sector (J) combines very high turnover with very high job destruction, making it difficult to classify as precarious in any meaningful sense. Moreover, excluding the two most obviously precarious sectors (G: retail and I: accommodation and food service) from the full sample leaves the main age results essentially unchanged (Annex Table C17). The precariousness channel therefore cannot be ruled out but is at best a partial explanation. More plausibly, the flattening of the inverted-U curve between workers' age and AI adoption may reflect the "skill leveling" effects of AI, whereby inexperienced workers benefit from AI support, and the boosting effects of AI on basic digital literacy, which is typically higher for young workers.

5. CONCLUSIONS AND POLICY IMPLICATIONS

Our analysis investigates the main obstacles to the spread of AI as well as the potential role public policies can play to overcome them. It uses a country/industry/time panel compiled from various sources, primarily responses to successive waves of the Eurostat survey on 'ICT usage and e-commerce in enterprises'. The data used in regressions cover 15 European countries and 24 industries over 2021–2025, yielding an unbalanced panel of 1,400 observations, which allows to control for country, industry, and year fixed effects and to trace the evolution of drivers over time. The diffusion of different types of AI varies greatly between countries and sectors, and the wealth of information provided by the Eurostat survey and the other sources we draw upon provides a basis for identifying the drivers of differences in AI adoption.

Mismatch obstacles (lack of AI expertise, poor data availability, and incompatibility with existing systems) are the most binding perceived barriers overall and particularly for extensive adoption. Our estimates suggest that a unit reduction in the share of firms perceiving mismatch obstacles is associated with well over 1 percentage point increase in the share of extensive AI adopters. However, the relative importance of these obstacles has evolved over time: personal concerns (legal uncertainty, ethical issues, data protection) were the dominant obstacles in the 2021–2024 period, reflecting uncertainties about a nascent technology, while mismatch obstacles have grown more salient as adoption has broadened. Perceived cost obstacles were also significant in the earlier period but have likely become increasingly intertwined with mismatch concerns over time.

Consistent with the importance of capabilities for technology adoption, organizational capital and ICT training and expertise are the strongest and most robust drivers of AI adoption: where these capabilities are abundant, adoption is significantly above average. Taken causally, our results suggest that extensive AI adoption rises one for one with organizational capital intensity and twice as much with the enhancement of available ICT skills.

Our findings also hint that the broader policy environment could have a bearing for AI diffusion in EU economies. We find that employment protection rules that limit labor market adaptability to technological change and regulations that thwart competition in key non-manufacturing services are linked with lower AI adoption. So does as well excessive regulation of digital markets, though this result is only tentative at this stage as it may reflect the influence of outliers. Especially, excessively strict employment protection rules in high churn sectors are consistently found to curb extensive AI adoption throughout our analysis. Conversely, policy that encourage or support innovation are found to boost such adoption.

Finally, there is evidence of an inverted U-curve between age and AI adoption: where the share of mature workers (aged 25-49) is higher, AI adoption also tends to be higher. This is consistent with the idea that both inexperienced and elderly workers may not be at ease with the use of AI. However, AI exposure lessens the negative association between young age and adoption likely due to the skill-leveling effect of the new technology.

Our analysis cannot claim to fully resolve all endogeneity concerns. Country and industry fixed effects, pre-sample measurement of drivers, instrumental variable estimation of contemporaneous perceived obstacles and the diff-in-diff approach to nation-wide regulations probably reduce but do not eliminate reverse causality. Further work with firm-level data and fully exogenous variation in AI drivers would strengthen causal inference. Nonetheless, the consistency of our findings across multiple specifications and robustness checks provides confidence that the identified associations are informative for policy design.

The results suggest a large room for policies aimed at helping AI diffusion in the EU:

- *Address the human capital gap*. The dominance of mismatch obstacles points to a key role for policies that improve AI literacy and skills across the workforce — not only ICT specialists but also managers, to build organizational absorption capacity. Given the inverted U-curve, targeted programs for youth and senior workers in less AI-exposed industries may be especially important.
- *Support R&D and innovation investment*. Innovation support seems positively associated with extensive adoption, suggesting that R&D incentives, subsidies for AI adoption, and support for SME access to AI tools and finance could raise the breadth of technology use.
- *Reform product market regulation*. Reducing anticompetitive regulatory burdens in key upstream industries (energy, communication, business services) could lower input costs and could increase incentives to offer and use AI-enabled services.
- *Make labor markets more adaptable*. Reforming excessively rigid employment protection rules, especially for firms in industries with higher workforce turnover, would reduce the organizational adjustment costs that currently deter adoption.
- *Clarify the legal and ethical framework*. While mismatch has overtaken personal concerns as the dominant obstacle over the sample period, legal and ethical uncertainty remains relevant. A clear, stable, and proportionate regulatory framework — such as that provided by the EU AI Act as it comes into effect — could reduce hesitation about adopting AI for business purposes.

The Draghi report (2024) highlighted Europe's lag relative to the United States in terms of productivity and GDP per capita level and growth. To prevent this gap from widening and to close it at least in part, it is important for EU countries to take full advantage of the emergence of AI and of the growth potential it can bring. The results of our analysis show that economic policy can play a major role in promoting the spread of AI. However, one difficulty here will be to coordinate national and European policies in a coherent and effective manner within the EU. This is undoubtedly one of the challenges facing Europe in the coming years.

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Annex

A. Basic data, coverage and sources

To conduct this study, we combine several complementary data sources in order to capture firms' adoption of artificial intelligence (AI), along with sectoral and national characteristics and the structural and regulatory environments that may shape this adoption. Information on AI adoption, perceived obstacles, firms' digital skills, and access to digital infrastructure is drawn from the Eurostat Survey on AI Adoption and ICT Usage in Enterprises (ISOC database). Data on tangible and intangible capital are taken from the EUKLEMS and INTANProd database developed by LUISS Lab, which covers both SNA and non-SNA intangible assets.

These datasets are complemented with a range of indicators from the OECD, including the Product Market Regulation (PMR) indicator, the Digital Market (DM) regulation indicator, the Employment Protection Legislation (EPL) indicator, United States input–output tables for several years, data on R&D tax incentives, and the Main Science and Technology Indicators (MSTI). We further incorporate information from additional sources, such as measures of sectoral digital intensity (Smiderle et al., 2026; Calvino et al., 2018), R&D expenditure (World Bank – World Development Indicators), job-level exposure to AI (Eloundou et al., 2024), and the age composition of the workforce in 2019 (Eurostat – Labour Force Survey).

The combination of these data sources yields a country–sector panel covering seventeen European countries—Austria, Belgium, Czech Republic, Germany, Denmark, Spain, Estonia, Finland, France, Greece, Italy, Lithuania, Latvia, the Netherlands, the Slovak Republic, Slovenia, and Sweden—across 24 industries. The full list of industries is reported in Table A1, while country-level aggregates are presented in Table A2.

Tables A3 and A4 provide a comprehensive overview of all variables used in the analysis, including their definitions, units of measurement, data sources, level of aggregation, and, where applicable, the indicators employed to proxy sectoral exposure.

Table A1: List of industries

<table>
<tr><th>Code NACE</th><th>Label</th><th colspan="2">Aggregation</th></tr>
<tr><td>C10–C12</td><td>Manufacture of food products; beverages and tobacco products</td><td rowspan="3">C10_C18</td><td rowspan="8"></td></tr>
<tr><td>C13–C15</td><td>Manufacture of textiles, wearing apparel, leather and related products</td></tr>
<tr><td>C16–C18</td><td>Manufacture of wood, paper, printing and reproduction</td></tr>
<tr><td>C19</td><td>Manufacture of coke and refined petroleum products</td><td rowspan="4">C19_C23</td></tr>
<tr><td>C20</td><td>Manufacture of chemicals and chemical products</td></tr>
<tr><td>C21</td><td>Manufacture of basic pharmaceutical products and pharmaceutical preparations</td></tr>
<tr><td>C22–C23</td><td>Manufacture of rubber and plastic products and other non-metallic mineral products</td></tr>
<tr><td>C24–C25</td><td>Manufacture of basic metals and fabricated metal products, except machinery and equipment</td><td>C24_C25</td></tr>
<tr><td>C26</td><td>Manufacture of computer, electronic and optical products</td><td>C26</td><td rowspan="5">C26_C33</td></tr>
<tr><td>C27</td><td>Manufacture of electrical equipment</td><td rowspan="2">C27_C28</td></tr>
<tr><td>C28</td><td>Manufacture of machinery and equipment n.e.c.</td></tr>
<tr><td>C29–C30</td><td>Manufacture of motor vehicles, trailers, semi-trailers and other transport equipment</td><td>C29_C30</td></tr>
<tr><td>C31–C33</td><td>Manufacture of furniture; jewellery, musical instruments, toys; repair and installation of machinery and equipment</td><td>C31_C33</td></tr>
<tr><td>D</td><td>Electricity, gas, steam and air conditioning supply</td><td rowspan="2">D_E</td><td rowspan="11"></td></tr>
<tr><td>E</td><td>Water supply; sewerage, waste management and remediation activities</td></tr>
<tr><td>F</td><td>Construction</td><td>F</td></tr>
<tr><td>G</td><td>Wholesale and retail trade; repair</td><td>G</td></tr>
<tr><td>H</td><td>Transportation and storage</td><td>H</td></tr>
<tr><td>I</td><td>Accommodation and food service activities</td><td>I</td></tr>
<tr><td>J58–J60</td><td>Publishing, audiovisual and broadcasting</td><td rowspan="3">J</td></tr>
<tr><td>J61</td><td>Telecommunications</td></tr>
<tr><td>J62–J63</td><td>IT and other information services</td></tr>
<tr><td>M</td><td>Professional, scientific and technical activities</td><td>M</td></tr>
<tr><td>N</td><td>Administrative and support service activities</td><td>N</td></tr>
</table>

Note: All missing values are replaced with the nearest higher-level sectoral aggregate. For example, if the variable value for C27 is missing for one country, it is replaced by the value of C27_C28 (the closest available aggregate). If this value is also missing, it is replaced by the next higher-level aggregate, C26_C33.

Table A2: Countries with sectoral aggregation

<table>
<tr><th>Code NACE</th><th>AT</th><th>BE</th><th>DE</th><th>ES</th><th>FI</th><th>IT</th><th>LT</th><th>SI</th></tr>
<tr><td>C10–C12</td><td></td><td></td><td rowspan="3">C10_C18
(all AI
obstacles)</td><td></td><td rowspan="3">C10_C18</td><td></td><td></td><td>C10_C18</td></tr>
<tr><td>C13–C15</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>C16–C18</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>C19</td><td>C19_C23</td><td></td><td>C19_C23</td><td></td><td rowspan="4">C19_C23</td><td rowspan="4">C19_C23
(all AI
obstacle)</td><td rowspan="4">C19_C23</td><td rowspan="4">C19_C23</td></tr>
<tr><td>C20</td><td></td><td></td><td></td><td></td></tr>
<tr><td>C21</td><td>C19_C23</td><td></td><td></td><td></td></tr>
<tr><td>C22–C23</td><td></td><td></td><td></td><td></td></tr>
<tr><td>C24–C25</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>C26</td><td></td><td></td><td rowspan="5">C26_C33
(all AI
obstacles)</td><td>C26_C33</td><td rowspan="5">C26_C33</td><td></td><td></td><td></td></tr>
<tr><td>C27</td><td></td><td></td><td></td><td rowspan="2">C27_C28
(all AI
obstacles)</td><td rowspan="2">C27_C28</td><td></td></tr>
<tr><td>C28</td><td></td><td></td><td></td><td></td></tr>
<tr><td>C29–C30</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>C31–C33</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>D</td><td></td><td rowspan="2">D_E
(E_AI_TPA)</td><td rowspan="2">D_E
(all AI
obstacles)</td><td rowspan="2">D_E</td><td rowspan="2">D_E
(E_AI_BEC)</td><td rowspan="2">D_E
(all AI
obstacles)</td><td rowspan="2">D_E</td><td></td></tr>
<tr><td>E</td><td></td><td></td></tr>
<tr><td>F</td><td></td><td></td><td>All AI
obstacles
Not available</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>G</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>H</td><td></td><td></td><td rowspan="7">All AI
obstacles
Not available</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>I</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>J58–J60</td><td></td><td rowspan="3">J
(E_AI_TTM)</td><td rowspan="3">J</td><td rowspan="3">J</td><td></td><td></td><td></td></tr>
<tr><td>J61</td><td>J</td><td></td><td></td><td>J</td></tr>
<tr><td>J62–J63</td><td></td><td></td><td></td><td></td></tr>
<tr><td>M</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>N</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
</table>

Note 1: The treatment applies only to AI technology and AI obstacle variables.
Note 2: DK, EE, EL, LV, NL, SE, and SK are available without the need for aggregation for AI data.

Table A3: Details of country*industry variables

Category	Variable Code	Variable Label	Source	Cover
AI technology	E_AI_TAR	Enterprises use AI technologies enabling physical movement of machines via autonomous decisions based on observation of surroundings (autonomous robots, …) (% of firms)	Isoc_eb_ain2 Eurostat	2021-2025
	E_AI_TIR	Enterprises use AI technologies identifying objects or persons based on images (image recognition, image processing) (% of firms)		
	E_AI_TML	Enterprises use machine learning (e.g. deep learning) for data analysis (% of firm)		
	E_AI_TNLG	Enterprises use AI technologies generating written or spoken language (natural language generation) (% of firms)		
	E_AI_TPA	Enterprises use AI technologies automating different workflows or assisting in decision making (AI based software robotic process automation) (% of firms)		
	E_AI_TSR	Enterprises use AI technologies converting spoken language into machine-readable format (speech recognition) (% of firms)		
	E_AI_TTM	Enterprises use AI technologies performing analysis of written language (text mining) (% of firms)		
	E_AI_TANY	Enterprises use at least one of the AI technologies: AI_TTM, AI_TSR, AI_TNLG, AI_TIR, AI_TML, AI_TPA, AI_TAR (% of firms)		
	E_AI_TGE2	Enterprises use at least two of the AI technologies: AI_TTM, AI_TSR, AI_TNLG, AI_TIR, AI_TML, AI_TPA, AI_TAR (% of firms)		
	E_AI_TGE3	Enterprises use at least three of the AI technologies: AI_TTM, AI_TSR, AI_TNLG, AI_TIR, AI_TML, AI_TPA, AI_TAR (% of firms)		
AI Obstacle - Personal concerns	E_AI_BLEG	Enterprises do not use AI technologies, because of a lack of clarity about the legal consequences (% of firms)		
	E_AI_BEC	Enterprises do not use AI technologies, because of ethical considerations (% of firms)		
	E_AI_BCDP	Enterprises do not use AI technologies, because of concerns regarding violation of data protection and privacy (% of firms)		
AI Obstacle - Costs concerns	E_AI_BCST	Enterprises do not use AI technologies, because the costs seem too high (% of firms)		
AI Obstacle - Mismatch with business	E_AI_BDDT	Enterprises do not use AI technologies, because of difficulties with availability or quality of the necessary data (% of firms)		
	E_AI_BLE	Enterprises do not use AI technologies, because of a lack of relevant expertise (% of firms)		
	E_AI_BNU	Enterprises do not use AI technologies, because artificial Intelligence technologies are not useful for Enterprise (% of firms)		
	E_AI_BINC	Enterprises do not use AI technologies, because of incompatibility with existing equipment, software or systems (% of firms)		
ICT /Training	$Train\_ICT_{ci}$	Firms that provided training to develop or upgrade the ICT skills of their personnel (% of firms)	Isoc_ske_ittn2 Eurostat	2018-2020 (mean)
	EMP_TIC_{ci}	Firms that employing ICT specialist (% of firms)	Isoc_ske_itspen2 Eurostat	
	EMP_TRAIN_ict	Firms that have employed ICT specialists and provided training to their staff to develop ICT skills (% of firms)	Isoc_ske_itspen2 Eurostat	
	$INT\_K\_Train_{ci}$	Intensity of training capital (measured as total training capital per hour worked)	EUKLEMS intangible account	2015-2019 (Mean)
	$INT\_K\_OrgCap_{ci}$	Intensity of organisational capital (measured as total organizational capital per hour)	EUKLEMS intangible account	
Accessibility to digital infrastructure	$INT50_{ci}$	Firms by sector in which at least 50% of employees have internet access (% of firms)	Isoc_c_in_en2 Eurostat	2018-2020 (mean)
	$INT1GB_{ci}$	The maximum contracted download speed of the fastest fixed line internet connection is at least 1 Gb/s (% of firms)	Isoc_ci_it_en2 Eurostat	
	WEB_{ci}	Firms with a website (% of firms)	Isoc_ciwebn2 Eurostat	
Other control	FIRM_SIZE	Firms size is computed following the approach of Pagano and Schivardi (2003), defined as the weighted average of the mean firm size within each size class, where weights correspond to the share of employment in each class.	Eurostat Structural Business Statistics	2021 to 2024
	OPENNESS	The openness indicator is calculated as the sum of absolute value of exports and imports at the country-sector level in 2022, divided by the total output in the same country-sector in 2022.	OECD I-O USA	2022

Table A4: Details of country variables crossed with sectoral exposure

Category	Variable code	Variable label	Source	Cover	Exposure (variable)	Exposure (source)
Competition policies	NMR_{ci}^{up}	Non-manufacturing Regulation index	OECD	2018	Intermediate consumption	I-O USA 2006 or 2018
	DM_{ci}^{d}	Digital market regulation index			Digital intensity (2018 USA)	Smiderle et al., 2026 indicator
Labor market regulation	EPL_{ci}^{d}	Employment Protection Legislation index	OECD	2018	$\left(\frac{LAB}{GO}\right)_i^{USA\ 2018}$	EUKLEMS& INTANProd
Innovative support	$BERD\_GOV\_GDP$	Business enterprise expenditure on R&D (BERD) financed by government, (% of GDP)	OECD MSTI and WDI	2018	Capital organisational intensity or Capital R&D intensity (2018 USA)	EUKLEMS& INTANProd
	$HERD\_GDP$	Higher education expenditure on R&D (% of GDP)				
	RND	Research and development expenditure (% of GDP)				
	$BINDEX\_LARGEF$	Implied tax subsidy rates on R&D tax incentives: profitable large firms				
	$BINDEX\_LARGEF\_LOSS$	Implied tax subsidy rates on R&D tax incentives: loss-making large firms				
	$BINDEX\_SMES$	Implied tax subsidy rates on R&D tax incentives: profitable SMEs				
	$BINDEX\_SMES\_LOSS$	Implied tax subsidy rates on R&D tax incentives: loss-making SMEs				
Other control	Trust	The measure of trust corresponds to the response to the following question: "Using this card, generally speaking, would you say that most people can be trusted, or that you can't be too careful in dealing with people? Please answer on a scale from 0 to 10, where 0 means that you can't be too careful and 10 means that most people can be trusted.	European Social Survey (ESS)	2018	USA Capital organisational intensity in 2018	EUKLEMS& INTANProd

B. Supplementary descriptives statistics

Figure B1: Evolution of AI adoption between 2021 and 2025

% of firms - country*industry average without FR and CZ

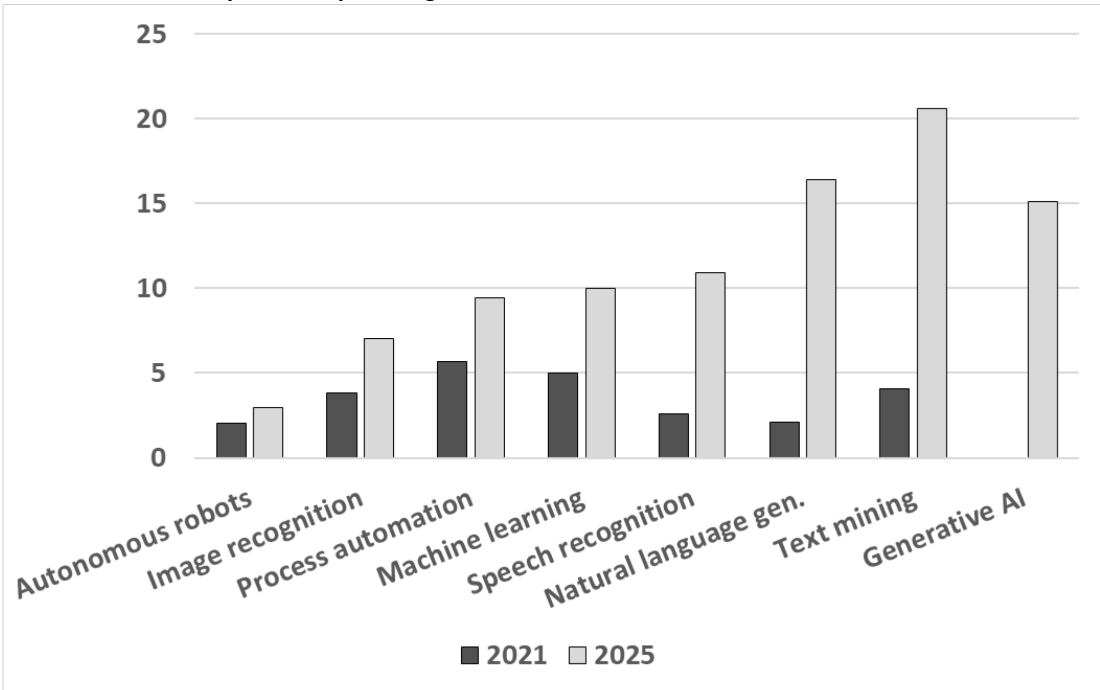


Figure B2: Level of regulation (OECD index at national level), for 2018

(each index scores 0 to 6, increasing in anticompetitive regulations)

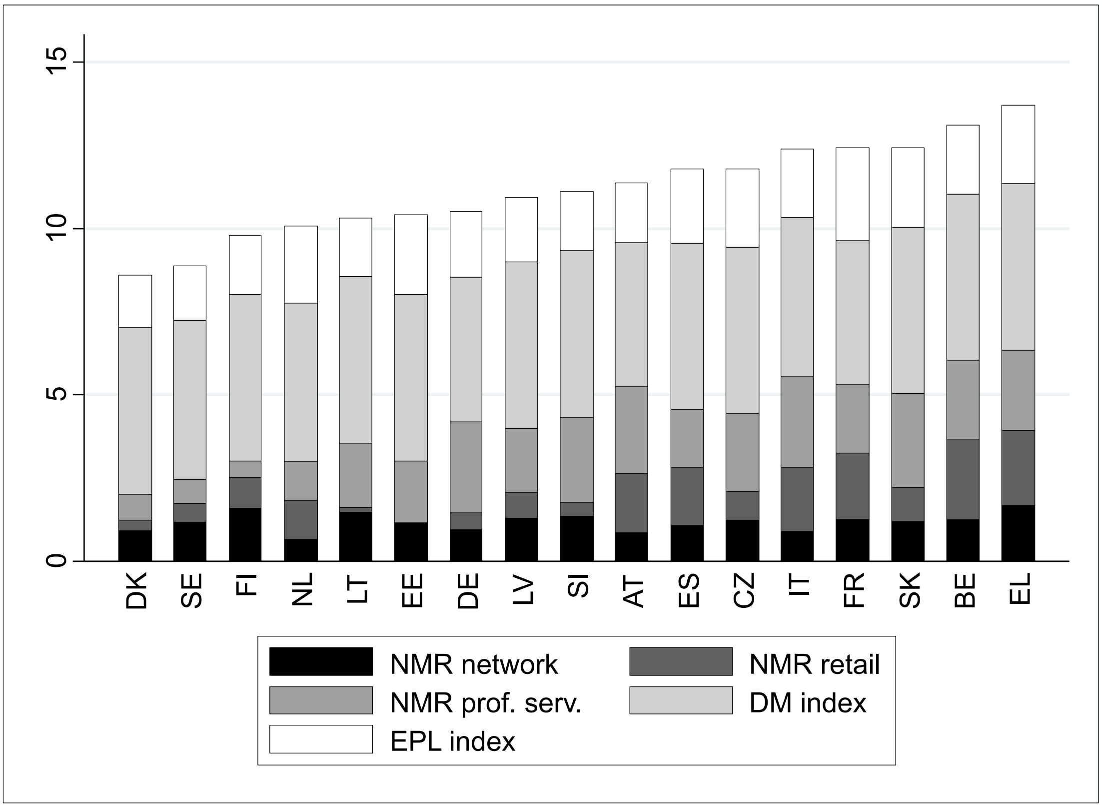


Figure B3: ICT training/specialists (ISOC database index), country average for 2018-2020

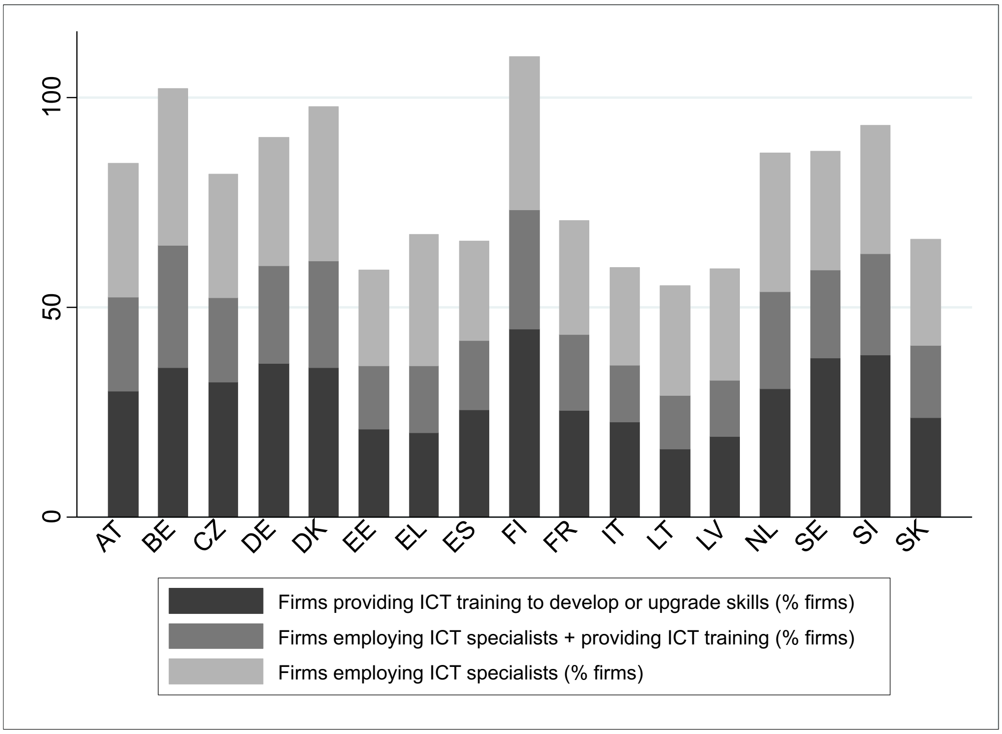


Figure B4: Access to digital infrastructure (ISOC database index), country average for 2018-2020

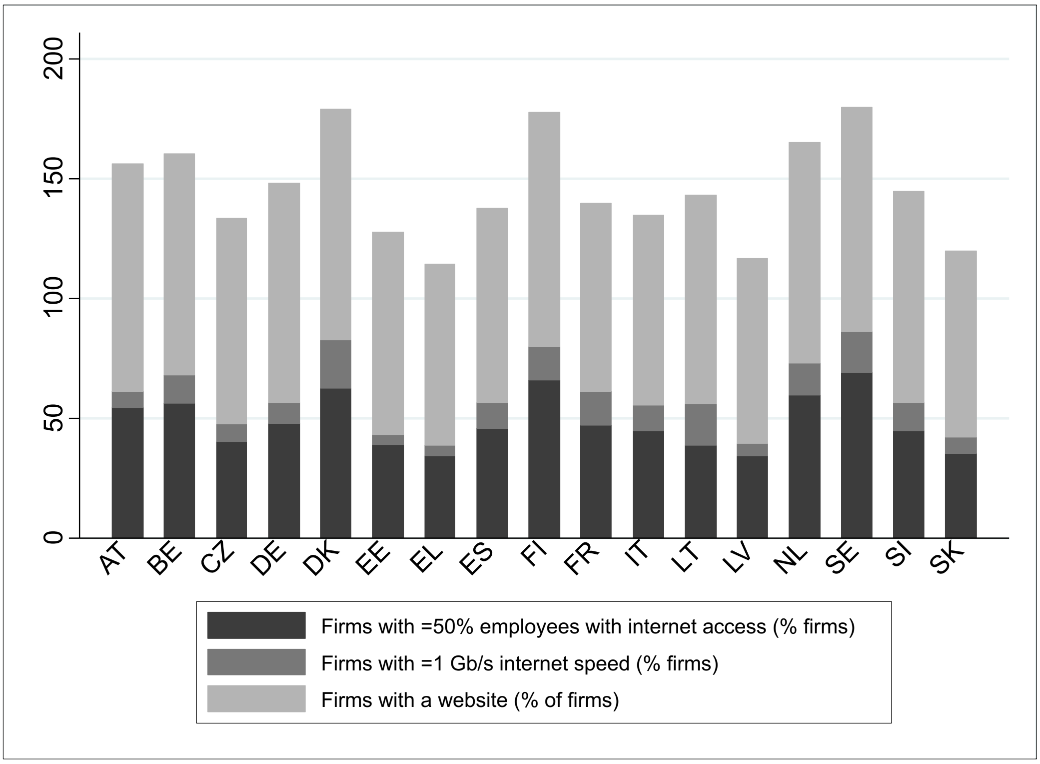
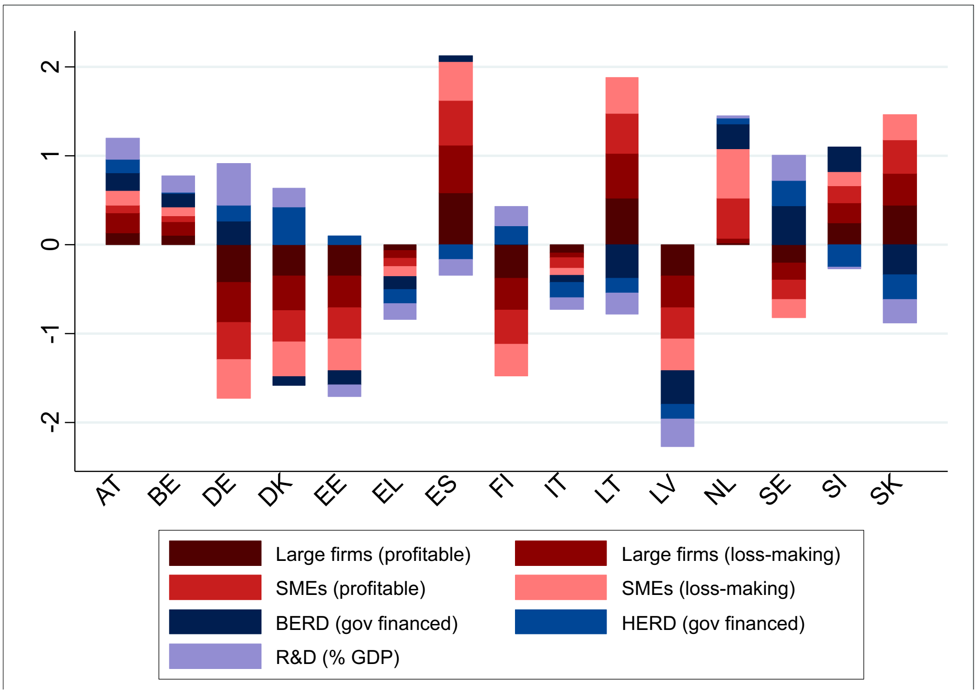


Figure B5: Innovation support (OECD MSTI and WDI index at national level), for 2018



Note: Variables are standardized for comparison.
Lecture: Variables related to R&D expenditure are shown in blue, while those related to the implied tax subsidy rate on R&D are shown in red. For all variables, a positive value indicates that the country is above the average of the countries included in the sample, whereas a negative value indicates that it is below this average. The observed differences therefore reflect each country's relative position within the sample.

Figure B6: Intangible capital intensity (EUKLEMS&IntantProd Database), 2015-2019 average, by country
Thousand dollars per hour worked

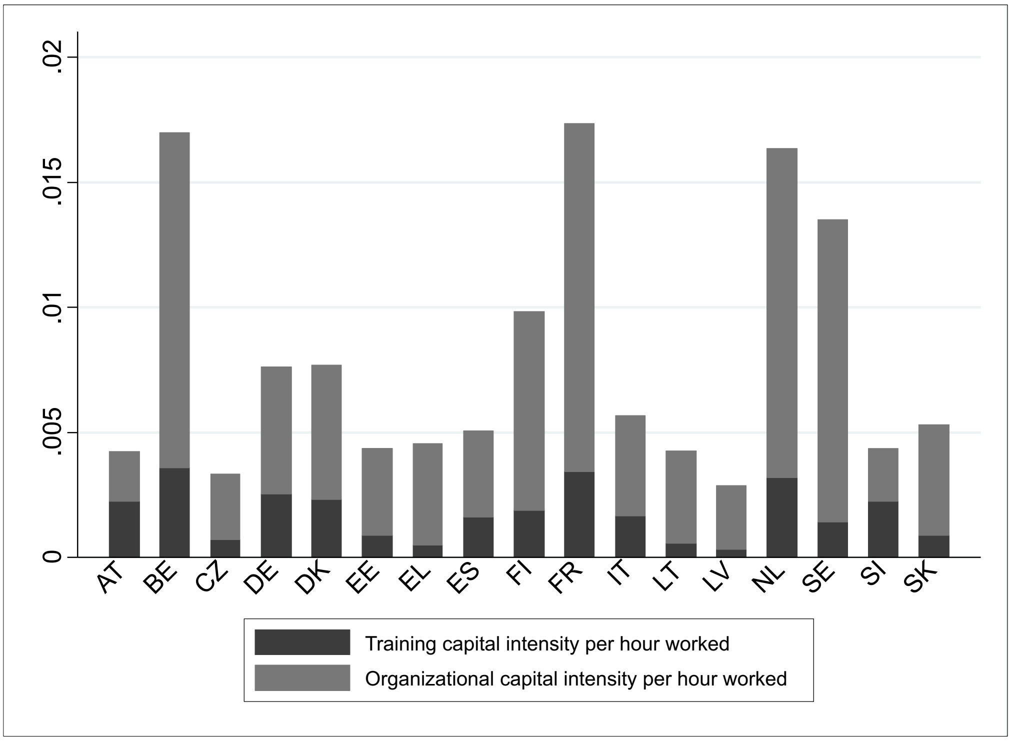
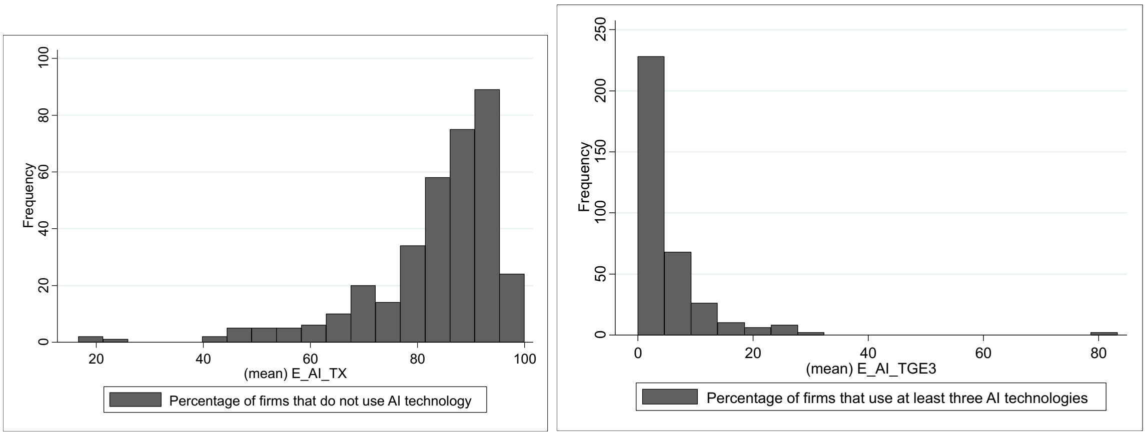


Table B7: Summary statistics

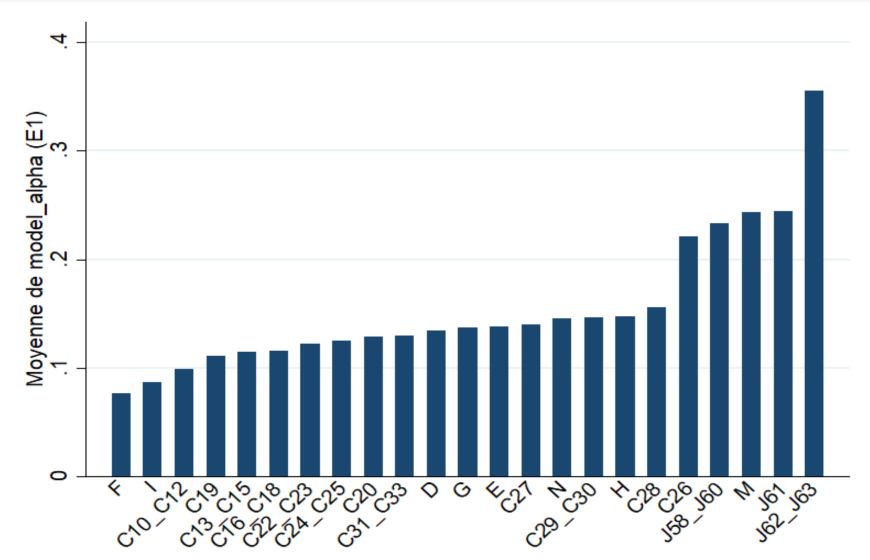
Variable	Obs	Mean	Std. Dev.	Min	Max
No AI adoption (%)	1,400	19.32	16.77	0	100
Adoption (PC1)	1,400	0.066	2.337	-1.946	29.213
At least three AI technologies (%)	1,400	7.62	11.03	0	83.33
Obstacle (PC1)	1,400	0	2.201	-3.158	21.543
Cost obstacle$_{ci}$	1,400	4.13	3.119	0	33.33
Personal obstacle$_{ci}$(PC1)	1,400	0	2.201	-3.158	21.543
Mismatch obstacle$_{ci}$(PC1)	1,400	0	2.201	-2.434	9.933
Train ICT$_{c}$(PC1)$_{i}$	1,400	0	1.709	-2.199	6.57
Organisational capital intensity (log)$_{ci}$	1,400	.006	.008	0	.101
Digital access$_{ci}$ (PC1)	1,400	.018	1.406	-3.059	6.391
Innovation support$_{ci}$(PC1)	1,400	-.074	2.101	-1.033	13.549
Regulatory burden$_{ci}$	1,400	.21	.106	.04	.565
Digital regulation$_{c}$* digital intensity$_{i}$	1,400	.462	.252	.128	1.083
EPL$_{c}$* churn$_{i}$	1,400	.440	.138	.219	.813
Share age 15-24$_{ci}$ (%)	1,400	8.045	4.938	1.578	42.121
Share age 25-49$_{ci}$ (%)	1,400	61.606	8.06	32.836	86.935
Share age 50+$_{ci}$ (%)	1,400	32.118	8.729	5.025	65.625

Figure B8: Distribution of firms that do not use AI or use at least three AI technologies



Source: Authors

Figure B9: Proportion of jobs potentially exposed to AI
Proportion of jobs



Source: Computed by the authors using the Eloundou et al. (2024) indicator.

Table B10-a: Matrix of correlations AI technologies

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) E_AI_TAR	1.000						
(2) E_AI_TSR	0.480	1.000					
(3) E_AI_TIR	0.594	0.606	1.000				
(4) E_AI_TNLG	0.401	0.847	0.592	1.000			
(5) E_AI_TML	0.497	0.772	0.736	0.757	1.000		
(6) E_AI_TPA	0.647	0.740	0.676	0.711	0.850	1.000	
(7) E_AI_TTM	0.463	0.851	0.543	0.875	0.741	0.720	1.000

Table B10-b: Matrix of correlations personal obstacle

Variables	(1)	(2)	(3)
(1) E_AI_BEC	1.000		
(2) E_AI_BCDP	0.570	1.000	
(3) E_AI_BLEG	0.736	0.831	1.000

Table B10-c: Matrix of correlations mismatch obstacle

Variables	(1)	(2)	(3)	(4)
(1) E_AI_BDDT	1.000			
(2) E_AI_BINC	0.784	1.000		
(3) E_AI_BLE	0.743	0.658	1.000	
(4) E_AI_BNU	0.325	0.343	0.399	1.000

Table B11: PCA Results

AI TECHNOLOGY

Principal components/correlation Number of obs = 1400
Number of comp. = 7
Trace = 7
Rotation: (unrotated = principal) Rho = 1.0000

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	5.071	4.253	**0.724**	0.724
Comp2	0.818	0.383	0.117	0.841
Comp3	0.435	0.140	0.062	0.903
Comp4	0.296	0.140	0.042	0.946
Comp5	0.156	0.037	0.022	0.968
Comp6	0.119	0.015	0.017	0.985
Comp7	0.105	.	0.015	1.000

Principal components (eigenvectors)

Variable	Higher values of the variable indicate:	Comp1	Comp2
E_AI_TAR	a higher percentage of firms using AI technologies that enable the physical movement of machines	0.294	0.703
E_AI_TIR	a higher percentage of firms using AI technologies that identify objects or persons based on images	0.351	0.376
E_AI_TML	a higher percentage of firms using machine learning techniques for data analysis	0.403	-0.018
E_AI_TNLG	a higher percentage of firms using AI technologies that generate written or spoken language	0.392	-0.382
E_AI_TPA	a higher percentage of firms using AI technologies to automate workflows or assist in decision-making	0.400	0.156
E_AI_TSR	a higher percentage of firms using AI technologies that convert spoken language into machine-readable format	0.400	-0.272
E_AI_TTM	a higher percentage of firms using AI technologies that analyze written language (text mining)	0.392	-0.346

AI OBSTACLE

Principal components/correlation Number of obs = 1400
Number of comp. = 8
Trace = 8
Rotation: (unrotated = principal) Rho = 1.0000

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	4.846	3.926	**0.606**	0.606
Comp2	0.920	0.206	0.115	0.721
Comp3	0.714	0.171	0.089	0.810
Comp4	0.543	0.161	0.068	0.878
Comp5	0.382	0.096	0.048	0.926
Comp6	0.286	0.102	0.036	0.962
Comp7	0.184	0.061	0.023	0.985
Comp8	0.123	.	0.015	1.000

Principal components (eigenvectors)

Variable	Higher values of the variable indicate:	Comp1	Comp2
E_AI_BCDP	a higher percentage of firms that do not use AI technologies due to concerns about data protection and privacy	0.378	-0.144
E_AI_BCST	a higher percentage of firms that do not use AI technologies because the costs are perceived as too high	0.281	0.600
E_AI_BDDT	a higher percentage of firms that do not use AI technologies due to difficulties related to the availability or quality data	0.385	-0.101
E_AI_BEC	a higher percentage of firms that do not use AI technologies due to ethical considerations	0.338	-0.326
E_AI_BINC	a higher percentage of firms that do not use AI technologies due to incompatibility with existing equipment, software, or systems	0.368	-0.002
E_AI_BLE	a higher percentage of firms that do not use AI technologies due to a lack of relevant expertise	0.398	-0.043
E_AI_BLEG	a higher percentage of firms that do not use AI technologies due to a lack of clarity regarding the legal implications	0.405	-0.260
E_AI_BNU	a higher percentage of firms that do not use AI technologies because they are not considered useful for the enterprise	0.240	0.658

AI OBSTACLE – PERSONAL CONCERNS

Principal components/correlation Number of obs = 1400
Number of comp. = 3
Trace = 3
Rotation: (unrotated = principal) Rho = 1.0000

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	2.430	1.991	**0.810**	0.810
Comp2	0.439	0.308	0.146	0.956
Comp3	0.131	.	0.044	1.000

Principal components (eigenvectors)

Variable	Higher values of the variable indicate:	Comp1	Comp2
E_AI_BCDP	a higher percentage of firms that do not use AI technologies due to concerns about data protection and privacy	0.573	-0.609
E_AI_BEC	a higher percentage of firms that do not use AI technologies due to ethical considerations	0.544	0.783
E_AI_BLEG	a higher percentage of firms that do not use AI technologies due to a lack of clarity regarding the legal implications	0.613	-0.126

AI OBSTACLE – MISMATCH WITH BUSINESS

Principal components/correlation Number of obs = 1400
Number of comp. = 4
Trace = 4
Rotation: (unrotated = principal) Rho = 1.0000

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	2.682	1.899	**0.671**	0.671
Comp2	0.784	0.444	0.196	0.867
Comp3	0.340	0.146	0.085	0.952
Comp4	0.194	.	0.049	1.000

Principal components (eigenvectors)

Variable	Higher values of the variable indicate:	Comp1	Comp2
E_AI_BDDT	a higher percentage of firms that do not use AI technologies due to difficulties related to the availability or quality data	0.553	-0.272
E_AI_BINC	a higher percentage of firms that do not use AI technologies due to incompatibility with existing equipment, software, or systems	0.537	-0.229
E_AI_BLE	a higher percentage of firms that do not use AI technologies due to a lack of relevant expertise	0.536	-0.087
E_AI_BNU	a higher percentage of firms that do not use AI technologies because they are not considered useful for the enterprise	0.343	0.931

TRAIN ICT AND EXPERTISE

Principal components/correlation Number of obs = 1400
Number of comp. = 4 Trace = 4
Rotation: (unrotated = principal) Rho = 1.0000

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	2.920	2.025	**0.730**	0.730
Comp2	0.896	0.765	0.224	0.954
Comp3	0.131	0.077	0.033	0.987
Comp4	0.054	.	0.013	1.000

Principal components (eigenvectors)

Variable	Higher values of the variable indicate:	Comp1	Comp2
zINT_K_Train	a higher level of training capital per hour worked	0.233	0.969
zTRAIN_IC~20	a higher percentage of firms that provided training to develop or upgrade the ICT skills of their personnel	0.559	-0.075
zEMP_TRAI~20	a higher percentage of firms that both employ ICT specialists and provide training to develop ICT skills among their staff	0.570	-0.132
zEMP_TIC1~20	a higher percentage of firms that employ ICT specialists	0.556	-0.195

ACCESS TO DIGITAL INFRASTRUCTURE

Principal components/correlation Number of obs = 1400
Number of comp. = 3 Trace = 3
Rotation: (unrotated = principal) Rho = 1.0000

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	1.961	1.311	**0.654**	0.654
Comp2	0.650	0.262	0.217	0.871
Comp3	0.389	.	0.130	1.000

Principal components (eigenvectors)

Variable	Higher values of the variable indicate:	Comp1	Comp2
zINT5018_20	a higher percentage of firms in which at least half of employees have access to the internet	0.622	-0.117
zINT1GB18_20	a higher percentage of firms whose fastest fixed-line internet connection has a maximum contracted download speed of at least 1 Gb/s	0.572	-0.608
zWEB18_20	a higher percentage of firms that have their own website	0.535	0.786

INNOVATION SUPPORT

Principal components/correlation Number of obs = 1400
Number of comp. = 6
Trace = 7
Rotation: (unrotated = principal) Rho = 1.0000

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	5.206	3.665	**0.744**	0.744
Comp2	1.541	1.396	0.220	0.964
Comp3	0.145	0.062	0.021	0.985
Comp4	0.083	0.065	0.012	0.997
Comp5	0.018	0.012	0.003	0.999
Comp6	0.006	0.006	0.001	1.000

Principal components (eigenvectors)

Variable	Higher values of the variable indicate:	Comp1	Comp2
zBINDEX_L~Fs	Higher implied tax subsidy rate on R&D (profitable large firms)	0.395	-0.324
zBINDEX_L~Ss	Higher implied tax subsidy rate on R&D (loss-making large firms)	0.403	-0.294
zBINDEX_~ESs	Higher implied tax subsidy rate on R&D (profitable SMEs)	0.404	-0.296
zBIN~S_LOSSs	Higher implied tax subsidy rate on R&D (los-making SMEs)	0.407	-0.260
zBERD_GOV_~s	Higher R&D expenditure	0.365	0.380
zHERD_GDPs	Higher higher-education expenditure on R&D	0.320	0.512
zRND_PC_WDIs	Higher R&D expenditure	0.341	0.496

C. Additional regression results and sensitivity analysis

Table C1: Main results - Panel regressions (2021-2025) with FR and CZ

VARIABLES	No AI adoption (1)	PC1 AI adoption (2)	Extensive AI adoption (3)
Organisational capital$_{ci0}$	-0.044	0.128*	0.120*
	(0.044)	(0.076)	(0.081)
ICT training & expertise$_{ci0}$ (PC1)	-0.287***	0.240***	0.218***
	(0.079)	(0.069)	(0.063)
Digital access$_{ci0}$ (PC1)	-0.013	0.084	0.082
	(0.070)	(0.069)	(0.061)
Innovation support$_{ci0}$(PC1)	0.013	0.032	0.047
	(0.036)	(0.053)	(0.044)
Regulatory burden$_{ci0}$	0.003	-0.088*	-0.066
	(0.048)	(0.050)	(0.050)
DM * digital intensity$_{ci0}$	0.793***	-0.251	-0.215
	(0.298)	(0.358)	(0.368)
EPL$_c$* churn$_{ci0}$	0.197	-0.387**	-0.445***
	(0.150)	(0.161)	(0.163)
Share age 25-49$_{ci0}$	-0.059*	0.078	0.072*
	(0.033)	(0.051)	(0.041)
Constant	1.570***	-0.883*	-0.910*
	(0.413)	(0.463)	(0.470)
Observations	1,592	1,592	1,592
R-squared	0.701	0.611	0.594
Country FE	yes	yes	yes
Industry FE	yes	yes	yes
Year FE	yes	yes	yes

Robust standard errors in parentheses (clustered at country×industry).
**** p<0.01, ** p<0.05, * p<0.1.*

Table C2: Robustness to the introduction of generative AI technology

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Period	2021-2025	2021-2025	2025	2025	2025	2025	2025	2025
Number of AI technologies	7	7	7	7	7	7	8	8
PC1 construction	All year	All year	All year	All year	Only 2025	Only 2025	Only 2025	Only 2025
VARIABLES	PC1 AI adoption	PC1 AI adoption	PC1 AI adoption	PC1 AI adoption	PC1 AI adoption	PC1 AI adoption	PC1 AI adoption	PC1 AI adoption
Obstacle$_{cit}$ (PC1)	-0.120***		-0.127*		-0.098*		-0.091*	
	(0.036)		(0.065)		(0.050)		(0.049)	
zE_AI_BCST		-0.014		-0.003		-0.002		-0.004
		(0.027)		(0.065)		(0.050)		(0.049)
zOBS_perso		0.011		0.122		0.094		0.083
		(0.038)		(0.092)		(0.071)		(0.069)
zOBS_mismatch		-0.126***		-0.279***		-0.215***		-0.193**
		(0.038)		(0.100)		(0.076)		(0.076)
Organisational capital$_{ci}$	0.188***	0.185***	0.389***	0.396***	0.293***	0.299***	0.276***	0.281***
	(0.035)	(0.034)	(0.077)	(0.075)	(0.059)	(0.058)	(0.058)	(0.057)
Train ICT$_{ci}$ (PC1)	0.216***	0.221***	0.174	0.183	0.132	0.139	0.120	0.125
	(0.070)	(0.071)	(0.137)	(0.139)	(0.104)	(0.106)	(0.098)	(0.100)
Digital access$_{ci}$ (PC1)	0.052	0.050	-0.104	-0.104	-0.076	-0.076	-0.088	-0.087
	(0.070)	(0.070)	(0.153)	(0.147)	(0.117)	(0.113)	(0.112)	(0.109)
Innovation support$_{ci}$(PC1)	0.094	0.095	0.150	0.122	0.121	0.099	0.116	0.096
	(0.075)	(0.075)	(0.180)	(0.181)	(0.141)	(0.141)	(0.137)	(0.138)
Regulatory burden$_{ci}$	-0.104**	-0.107**	-0.150	-0.137	-0.117	-0.107	-0.091	-0.082
	(0.050)	(0.050)	(0.107)	(0.108)	(0.082)	(0.083)	(0.080)	(0.082)
DM * digital intensity$_{ci}$	-0.741*	-0.699*	-1.539**	-1.721***	-1.118**	-1.258**	-1.332**	-1.456***
	(0.390)	(0.389)	(0.702)	(0.664)	(0.533)	(0.504)	(0.542)	(0.515)
EPL$_c$* churn$_{ci}$	-0.492***	-0.476***	-0.830**	-0.833**	-0.631**	-0.634**	-0.602**	-0.603**
	(0.170)	(0.175)	(0.354)	(0.350)	(0.273)	(0.269)	(0.269)	(0.265)
Share age 25-49$_{ci}$	0.102*	0.102*	0.232*	0.220*	0.177*	0.167*	0.179*	0.170*
	(0.052)	(0.053)	(0.127)	(0.128)	(0.099)	(0.099)	(0.096)	(0.096)
Constant	-1.548***	-1.452***	-1.891**	-2.097***	-1.787***	-1.946***	-2.049***	-2.189***
	(0.469)	(0.479)	(0.842)	(0.801)	(0.639)	(0.608)	(0.645)	(0.617)
Observations	1,400	1,400	350	350	350	350	350	350
R-squared	0.629	0.631	0.711	0.718	0.702	0.708	0.717	0.723

Robust standard errors in parentheses (cluster: country*industry) ; *** p<0.01, ** p<0.05, * p<0.1

Reg. 1 to 4: these correspond to the first principal components (PC1) constructed over the 2021–2025 period, excluding generative media AI from the construction. Reg. 5 and 6: these correspond to the first principal components (PC1) constructed using only the year 2025, also excluding generative media AI from the construction. Reg. 7 and 8: these correspond to the first principal components (PC1) constructed using only the year 2025 and including generative media AI.

Table C3: Main results with all fixed effects

VARIABLES	No AI adoption (1)	PC1 AI adoption (2)	Extensive AI adoption (3)
$Obstacle_{cit}$ (PC1)	0.102***	-0.122**	-0.115***
	(0.033)	(0.051)	(0.039)
Organisational $capital_{ci}$	-0.075***	0.188***	0.180***
	(0.026)	(0.037)	(0.043)
Train ICT_{ci} (PC1)	-0.267***	0.217***	0.194***
	(0.083)	(0.073)	(0.066)
Digital $access_{ci}$ (PC1)	-0.007	0.051	0.049
	(0.076)	(0.074)	(0.063)
Innovation $support_{ci}$(PC1)	0.004	0.094	0.102*
	(0.040)	(0.078)	(0.061)
Regulatory $burden_{ci}$	0.015	-0.104**	-0.083
	(0.050)	(0.052)	(0.051)
DM * digital $intensity_{ci}$	1.244***	-0.741*	-0.787*
	(0.343)	(0.407)	(0.420)
EPL_c* $churn_{ci}$	0.234	-0.490***	-0.556***
	(0.180)	(0.173)	(0.176)
Share age 25-49_{ci}	-0.070**	0.102*	0.095**
	(0.035)	(0.055)	(0.042)
Constant	2.247***	-1.587***	-1.696***
	(0.461)	(0.485)	(0.488)
Observations	1,400	1,400	1,400
R-squared	0.804	0.722	0.742
Country FE	yes	yes	yes
Industry FE	yes	yes	yes
Year FE	yes	yes	yes
Country*year	yes	yes	yes
Industry*year	yes	yes	yes

Robust standard errors in parentheses (cluster: country*industry)
*** p<0.01, ** p<0.05, * p<0.1

Table C4: Robustness to different interaction for innovative support

Dependent variable	No AI adoption	PC1 AI adoption	Extensive AI adoption	No AI adoption	PC1 AI adoption	Extensive AI adoption	No AI adoption	PC1 AI adoption	Extensive AI adoption
Innovation support crossed with	R&D capital intensity (USA)	R&D capital intensity (USA)	R&D capital intensity (USA)	OrgCap intensity (USA)	OrgCap intensity (USA)	OrgCap intensity (USA)	Intangible capital intensity (USA)	Intangible capital intensity (USA)	Intangible capital intensity (USA)
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Obstacle_{cit}$ (PC1)	0.118***	-0.120***	-0.135***	0.116***	-0.116***	-0.132***	0.118***	-0.120***	-0.135***
	(0.026)	(0.036)	(0.029)	(0.026)	(0.034)	(0.028)	(0.026)	(0.036)	(0.029)
Organisational $capital_{ci0}$	-0.075***	0.188***	0.180***	-0.070***	0.179***	0.172***	-0.074***	0.187***	0.180***
	(0.025)	(0.035)	(0.040)	(0.025)	(0.033)	(0.039)	(0.025)	(0.035)	(0.040)
ICT training & $expertise_{ci0}$ (PC1)	-0.268***	0.216***	0.195***	-0.254***	0.186**	0.166**	-0.265***	0.208***	0.185***
	(0.079)	(0.070)	(0.063)	(0.078)	(0.073)	(0.065)	(0.080)	(0.071)	(0.064)
Digital $access_{ci0}$ (PC1)	-0.006	0.052	0.047	-0.011	0.057	0.052	-0.008	0.050	0.046
	(0.074)	(0.070)	(0.061)	(0.075)	(0.072)	(0.062)	(0.074)	(0.072)	(0.062)
Innovation $support_{ci0}$(PC1)	**0.005**	**0.094**	**0.102***	**-0.080**	**0.255***	**0.251*****	**-0.013**	**0.110**	**0.125****
	(0.038)	**(0.075)**	**(0.058)**	**(0.068)**	**(0.138)**	**(0.093)**	**(0.042)**	**(0.079)**	**(0.061)**
Regulatory $burden_{ci0}$	0.015	-0.104**	-0.083*	0.013	-0.089*	-0.068	0.016	-0.102**	-0.081*
	(0.047)	(0.050)	(0.049)	(0.046)	(0.046)	(0.046)	(0.047)	(0.049)	(0.048)
DM * digital $intensity_{ci0}$	1.245***	-0.741*	-0.788*	1.199***	-0.589	-0.637	1.239***	-0.688*	-0.728*
	(0.329)	(0.390)	(0.403)	(0.327)	(0.381)	(0.389)	(0.327)	(0.386)	(0.399)
EPL_c* $churn_{ci0}$	0.222	-0.492***	-0.541***	0.218	-0.482***	-0.531***	0.222	-0.492***	-0.540***
	(0.172)	(0.170)	(0.170)	(0.171)	(0.165)	(0.165)	(0.172)	(0.171)	(0.170)
Share age 25-49_{ci0}	-0.071**	0.102*	0.095**	-0.069**	0.093**	0.086**	-0.071**	0.102*	0.095**
	(0.034)	(0.052)	(0.040)	(0.032)	(0.045)	(0.035)	(0.033)	(0.052)	(0.039)
Constant	2.139***	-1.548***	-1.657***	2.109***	-1.469***	-1.581***	2.129***	-1.492***	-1.592***
	(0.440)	(0.469)	(0.473)	(0.438)	(0.453)	(0.460)	(0.438)	(0.460)	(0.467)
Observations	1,400	1,400	1,400	1,400	1,400	1,400	1,400	1,400	1,400
R-squared	0.711	0.629	0.616	0.712	0.636	0.622	0.711	0.630	0.617
Country FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes

Robust standard errors in parentheses (clustered at country×industry).
**** p<0.01, ** p<0.05, * p<0.1.*

Table C5: Main results with Digital Market regulation mean between 2018 and 2023

VARIABLES	No AI adoption (1)	PC1 AI adoption (2)	Extensive AI adoption (3)
$Obstacle_{cit}$ (PC1)	0.117***	-0.119***	-0.135***
	(0.026)	(0.036)	(0.029)
Organisational $capital_{ci0}$	-0.071***	0.187***	0.179***
	(0.025)	(0.035)	(0.041)
ICT training & $expertise_{ci0}$ (PC1)	-0.291***	0.226***	0.206***
	(0.078)	(0.069)	(0.063)
Digital $access_{ci0}$ (PC1)	-0.004	0.047	0.043
	(0.071)	(0.071)	(0.061)
Innovation $support_{ci0}$(PC1)	0.003	0.094	0.102*
	(0.039)	(0.075)	(0.059)
Regulatory $burden_{ci0}$	0.019	-0.108**	-0.087*
	(0.048)	(0.050)	(0.049)
DM * digital $intensity_{ci0}$	**1.066*** **	**-0.314**	**-0.359**
	(0.371)	**(0.380)**	**(0.380)**
EPL_c* $churn_{ci0}$	0.221	-0.499***	-0.547***
	(0.167)	(0.171)	(0.169)
Share age $25\text{-}49_{ci0}$	-0.063*	0.099*	0.092**
	(0.034)	(0.053)	(0.040)
Constant	1.796***	-1.012**	-1.113***
	(0.428)	(0.402)	(0.417)
Observations	1,400	1,400	1,400
R-squared	0.711	0.629	0.616
Country FE	yes	yes	yes
Industry FE	yes	yes	yes
Year FE	yes	yes	yes

Robust standard errors in parentheses (cluster: country*industry)
*** p<0.01, ** p<0.05, * p<0.1

Table C6 : Main results with bartik instrument obstacle

VARIABLES	No AI adoption (1)	PC1 AI adoption (2)	Extensive AI adoption (3)
$Obstacle_{cit}$ (PC1)	0.102***	-0.089*	-0.158**
	(0.038)	(0.049)	(0.062)
Organisational $capital_{ci}$	-0.072***	0.184***	0.176***
	(0.026)	(0.036)	(0.043)
Train ICT_{ci} (PC1)	-0.260***	0.209***	0.186***
	(0.081)	(0.072)	(0.066)
Digital $access_{ci}$ (PC1)	-0.016	0.061	0.059
	(0.072)	(0.068)	(0.057)
Innovation $support_{ci}$(PC1)	0.003	0.096	0.104*
	(0.040)	(0.078)	(0.062)
Regulatory $burden_{ci}$	0.016	-0.105**	-0.084
	(0.050)	(0.052)	(0.051)
DM * digital $intensity_{ci}$	1.242***	-0.738*	-0.784*
	(0.328)	(0.388)	(0.400)
EPL_c* $churn_{ci}$	0.321*	-0.591***	-0.658***
	(0.180)	(0.192)	(0.186)
Share age $25\text{-}49_{ci}$	-0.069**	0.100*	0.093**
	(0.034)	(0.053)	(0.041)
Constant	2.351***	-1.743***	-1.962***
	(0.437)	(0.469)	(0.474)
Observations	1,400	1,400	1,400
R-squared	0.706	0.622	0.612
Country FE	yes	yes	yes
Industry FE	yes	yes	yes
Year FE	yes	yes	yes

Robust standard errors in parentheses (cluster: country*industry)
*** p<0.01, ** p<0.05, * p<0.1

Table C7: Main results with other control

VARIABLES	No AI adoption (1)	PC1 AI adoption (2)	Extensive AI adoption (3)
Firm size$_{cit}$	-0.011	0.021	0.039
	(0.033)	(0.052)	(0.046)
ICT capital intensity$_{ci}$	-0.004	0.018	0.014
	(0.017)	(0.015)	(0.019)
Trust * USA OrgCap$_{ci}$	-0.095	0.078	0.120
	(0.179)	(0.189)	(0.214)
Openness indicator$_{ci}$	0.053***	-0.048*	-0.041
	(0.020)	(0.028)	(0.026)
Obstacle$_{cit}$ (PC1)	0.120***	-0.122***	-0.139***
	(0.026)	(0.034)	(0.028)
Organisational capital$_{ci}$	-0.060**	0.173***	0.164***
	(0.025)	(0.036)	(0.041)
Train ICT$_{ci}$ (PC1)	-0.279***	0.225***	0.199***
	(0.084)	(0.072)	(0.065)
Digital access$_{ci}$ (PC1)	-0.016	0.066	0.073
	(0.078)	(0.085)	(0.074)
Innovation support$_{ci}$(PC1)	0.000	0.099	0.108*
	(0.036)	(0.072)	(0.056)
Regulatory burden$_{ci}$	0.015	-0.100**	-0.078*
	(0.046)	(0.050)	(0.046)
DM * digital intensity$_{ci}$	1.179***	-0.566	-0.602
	(0.352)	(0.427)	(0.450)
EPL$_{c}$* churn$_{ci}$	0.214	-0.487***	-0.547***
	(0.169)	(0.159)	(0.155)
Share age 25-49$_{ci}$	-0.070**	0.100*	0.091**
	(0.034)	(0.056)	(0.043)
Constant	2.029***	-1.328**	-1.412**
	(0.474)	(0.536)	(0.565)
Observations	1,400	1,400	1,400
R-squared	0.714	0.632	0.619
Country FE	yes	yes	yes
Industry FE	yes	yes	yes
Year FE	yes	yes	yes

Robust standard errors in parentheses (cluster: country*industry)
*** p<0.01, ** p<0.05, * p<0.1

- Firm size is calculated following the approach of Pagano and Schivardi (2003), as the weighted average of the mean firm size in each size class, where the weights are given by the employment share of each class.

$$\sum_{g} \frac{emp_{gcit}}{unit_{gcit}} * \frac{emp_{gcit}}{emp_{cit}}$$

Where emp_{gcit} denotes the number of employees in size class 'g' industry 'i' country 'c'time 't'and $unit_{gcit}$ denotes the number of firms in size class 'g' industry 'i' country 'c' time 't'. The data are available for the years 2021, 2023, and 2024. For 2025, we assume that the 2024 values remain unchanged and therefore replicate the 2024 observations.

Firm size classes 'g' are defined as follows: 0–1, 2–9, 10–19, 20–49, 50–249, and 250 or more employees.. Source Eurostat Structural Business Statistics

- Since the trust variable is measured at the country level for the year 2018, we interact it with organizational capital intensity across sectors in the United States in 2018.

- The trade openness indicator is calculated as follows:

$$\frac{\left|X_{ci}^{2022} + M_{ci}^{2022}\right|}{OUTPUT_{ci}^{2022}}$$

Source tables input-output: OECD

Table C8: Main results with temporal dimension

VARIABLES	No AI adoption (1)	PC1 AI adoption (2)	Extensive AI adoption (3)
$Obstacle_{cit}$ (PC1)	0.141***	-0.150***	-0.158***
	(0.034)	(0.046)	(0.035)
(Lag4) Organisational $capital_{ci}$	-0.011	0.113***	0.131***
	(0.022)	(0.030)	(0.035)
(Lag1) Train ICT_{ci} (PC1)	-0.351***	0.371***	0.343***
	(0.073)	(0.123)	(0.094)
Digital $access_{ci}$ (PC1)	-0.104	0.167*	0.114
	(0.090)	(0.100)	(0.081)
(Lag4) Innovation $support_{ci}$(PC1)	0.009	0.069	0.109*
	(0.026)	(0.050)	(0.064)
(Lag2) Regulatory $burden_{ci}$	0.072	-0.147**	-0.101*
	(0.053)	(0.065)	(0.059)
(Lag2) DM * digital $intensity_{ci}$	0.560***	-0.688***	-0.795***
	(0.056)	(0.052)	(0.069)
(Lag6) EPL_c* $churn_{ci}$	0.072	-0.179***	-0.193***
	(0.049)	(0.060)	(0.062)
(Lag2) Share age $25\text{-}49_{ci}$	-0.041	0.051*	0.044*
	(0.027)	(0.027)	(0.027)
Constant	0.367***	-0.197	-0.276*
	(0.122)	(0.176)	(0.150)
Observations	1,613	1,613	1,613
R-squared	0.763	0.695	0.686
Country FE	yes	yes	yes
Industry FE	yes	yes	yes
Year FE	yes	yes	yes

Robust standard errors in parentheses (cluster: country*industry)*** p<0.01, ** p<0.05, * p<0.1
Note: For regressions incorporating the time dimension, the sample comprises 1,613 observations.
This is because the missing 2022 values were interpolated between the 2021 and 2023 observations.

Table C9: sensitivity to other measure of interaction for EPL

VARIABLES	No AI adoption (1)	PC1 AI adoption (2)	Extensive AI adoption (3)	No AI adoption (4)	PC1 AI adoption (5)	Extensive AI adoption (6)	No AI adoption (7)	PC1 AI adoption (8)	Extensive AI adoption (9)
$Obstacle_{cit}$ (PC1)	0.118***	-0.120***	-0.135***	0.117***	-0.119***	-0.135***	0.118***	-0.123***	-0.140***
	(0.026)	(0.036)	(0.029)	(0.026)	(0.036)	(0.029)	(0.026)	(0.036)	(0.030)
Organisational $capital_{ci}$	-0.075***	0.188***	0.180***	-0.076***	0.189***	0.182***	-0.076***	0.189***	0.182***
	(0.025)	(0.035)	(0.040)	(0.025)	(0.035)	(0.040)	(0.024)	(0.033)	(0.038)
Train ICT_{ci} (PC1)	-0.268***	0.216***	0.195***	-0.265***	0.209***	0.187***	-0.275***	0.223***	0.199***
	(0.079)	(0.070)	(0.063)	(0.079)	(0.069)	(0.063)	(0.078)	(0.070)	(0.064)
Digital $access_{ci}$ (PC1)	-0.006	0.052	0.047	-0.003	0.047	0.043	0.004	0.040	0.039
	(0.074)	(0.070)	(0.061)	(0.074)	(0.071)	(0.061)	(0.072)	(0.071)	(0.062)
Innovation $support_{ci}$(PC1)	0.005	0.094	0.102*	0.005	0.094	0.102*	0.006	0.093	0.101*
	(0.038)	(0.075)	(0.058)	(0.038)	(0.075)	(0.059)	(0.037)	(0.074)	(0.058)
Regulatory $burden_{ci}$	0.015	-0.104**	-0.083*	0.016	-0.103**	-0.082*	0.019	-0.107**	-0.084*
	(0.047)	(0.050)	(0.049)	(0.047)	(0.050)	(0.049)	(0.047)	(0.051)	(0.050)
DM * digital $intensity_{ci}$	1.245***	-0.741*	-0.788*	1.220***	-0.714*	-0.760*	1.197***	-0.703*	-0.770*
	(0.329)	(0.390)	(0.403)	(0.324)	(0.387)	(0.402)	(0.338)	(0.396)	(0.404)
EPL_c* $churn_{ci}$	0.222	-0.492***	-0.541***						
	(0.172)	(0.170)	(0.170)						
EPL_c* $exit\_rate_{ci}$				0.291*	-0.526***	-0.567***			
				(0.168)	(0.164)	(0.161)			
EPL_c* $(LAB/GO)_{ci}$							0.302*	-0.444**	-0.403**
							(0.174)	(0.220)	(0.213)
Share age $25\text{-}49_{ci}$	-0.071**	0.102*	0.095**	-0.071**	0.102*	0.095**	-0.071**	0.101*	0.093**
	(0.034)	(0.052)	(0.040)	(0.033)	(0.052)	(0.040)	(0.033)	(0.052)	(0.040)
Constant	2.139***	-1.548***	-1.657***	2.276***	-1.735***	-1.851***	2.317***	-1.697***	-1.727***
	(0.440)	(0.469)	(0.473)	(0.454)	(0.472)	(0.477)	(0.449)	(0.523)	(0.526)
Observations	1,400	1,400	1,400	1,400	1,400	1,400	1,400	1,400	1,400
R-squared	0.711	0.629	0.616	0.712	0.630	0.617	0.712	0.629	0.614
Country FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes

Robust standard errors in parentheses (cluster: country*industry)
*** p<0.01, ** p<0.05, * p<0.1

Note : *EPLd × churn*, *EPLd × exit rate* et *EPLd × (LAB/GO)* correspond to the interactions between EPL (country-year) and, respectively, job turnover, job exit rate, and the labor compensation-to-gross output ratio (measured in the United States in 2017).

Table C10: Age variable interacted with capital intensity in organizational capital

VARIABLES	No AI adoption (1)	No AI adoption (2)	PC1 AI adoption (3)	PC1 AI adoption (4)	Extensive adoption (5)	Extensive adoption (6)
Share age 15-24$_{ci}$	0.091***		-0.125***		-0.122***	
	(0.034)		(0.047)		(0.040)	
Share age 50+$_{ci}$	0.027		-0.060		-0.055*	
	(0.034)		(0.044)		(0.032)	
Share age 15-24$_{ci}$*OrgCap	-0.061		0.176**		0.165**	
	(0.071)		(0.089)		(0.077)	
Share age 50+$_{ci}$*OrgCap	0.001		-0.023		-0.008	
	(0.079)		(0.098)		(0.088)	
Share age 25-49$_{ci}$		-0.062*		0.080*		0.075**
		(0.033)		(0.047)		(0.038)
Share age 25-49$_{ci}$ *OrgCap		-0.084***		0.209***		0.195***
		(0.024)		(0.041)		(0.036)
Constant	2.056***	2.144***	-1.534***	-1.563***	-1.627***	-1.672***
	(0.433)	(0.440)	(0.491)	(0.469)	(0.485)	(0.472)
Observations	1,400	1,400	1,400	1,400	1,400	1,400
R-squared	0.710	0.712	0.621	0.634	0.610	0.620
Country FE	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes

Robust standard errors in parentheses (cluster: country*industry)
*** p<0.01, ** p<0.05, * p<0.1
All specifications include the full set of control variables.

Table C11: Supplementary analysis for firm size

VARIABLES	Extensive AI adoption (1)	Extensive AI adoption (2)	Extensive AI adoption (3)	Extensive AI adoption (4)	Extensive AI adoption (5)
Obstacle$_{cit}$ (PC1)	-0.139***				
	(0.028)				
Firm size$_{cit}$	0.039	0.033	0.051	0.108***	0.122**
	(0.046)	(0.046)	(0.046)	(0.041)	(0.050)
ICT capital intensity$_{ci}$	0.014	0.014			
	(0.019)	(0.018)			
Trust * USA OrgCap$_{ci}$	0.120	0.085			
	(0.214)	(0.223)			
Openness indicator$_{ci}$	-0.041	-0.041			
	(0.026)	(0.026)			
Organisational capital$_{ci}$	0.164***	0.162***			
	(0.041)	(0.043)			
Train ICT$_{ci}$ (PC1)	0.199***	0.193***			
	(0.065)	(0.068)			
Digital access$_{ci}$ (PC1)	0.073	0.076			
	(0.074)	(0.071)			
Innovation support$_{ci}$(PC1)	0.108*	0.109*			
	(0.056)	(0.059)			
Regulatory burden$_{ci}$	-0.078*	-0.078*			
	(0.046)	(0.047)			
DM * digital intensity$_{ci}$	-0.602	-0.620			
	(0.450)	(0.452)			
EPL$_{c}$* churn$_{ci}$	-0.547***	-0.646***			
	(0.155)	(0.169)			
Share age 25-49$_{ci}$	0.091**	0.090**			
	(0.043)	(0.044)			
Constant	-1.412**	-1.519***	-0.598***	-0.209	-0.752***
	(0.565)	(0.571)	(0.078)	(0.138)	(0.059)
Observations	1,400	1,400	1,400	1,400	1,400
R-squared	0.619	0.607	0.564	0.273	0.495
Country FE	yes	yes	yes	yes	no
Industry FE	yes	yes	yes	no	yes
Year FE	yes	yes	yes	yes	yes

Robust standard errors in parentheses (cluster: country*industry)
*** p<0.01, ** p<0.05, * p<0.1

Table C12-a: Sensitivity to country exclusion

(dependent variable: extensive AI adoption)

VARIABLES	(1) AT	(2) BE	(3) DE	(4) DK	(5) EE	(6) EL	(7) ES	(8) FI	(9) IT	(10) LT	(11) LV	(12) NL	(13) SE	(14) SI	(15) SK
Obstacle$_{cit}$ (PC1)	-0.139***	-0.134***	-0.135***	-0.142***	-0.134***	-0.144***	-0.121***	-0.130***	-0.135***	-0.134***	-0.139***	-0.130***	-0.117***	-0.158***	-0.140***
	(0.030)	(0.032)	(0.029)	(0.034)	(0.030)	(0.030)	(0.023)	(0.030)	(0.029)	(0.030)	(0.030)	(0.029)	(0.030)	(0.033)	(0.033)
Organisational capital$_{ci}$	0.186***	0.186***	0.186***	0.184***	0.172***	0.182***	0.166***	0.182***	0.178***	0.173***	0.177***	0.219***	0.181***	0.169***	0.202***
	(0.038)	(0.038)	(0.039)	(0.039)	(0.042)	(0.041)	(0.049)	(0.042)	(0.040)	(0.042)	(0.042)	(0.033)	(0.043)	(0.040)	(0.035)
Train ICT$_{ci}$ (PC1)	0.235***	0.235***	0.196***	0.179***	0.187***	0.182***	0.216***	0.132**	0.173***	0.191***	0.186***	0.206***	0.200***	0.224***	0.192***
	(0.067)	(0.073)	(0.065)	(0.065)	(0.068)	(0.067)	(0.062)	(0.059)	(0.065)	(0.065)	(0.064)	(0.065)	(0.067)	(0.067)	(0.064)
Digital access$_{ci}$ (PC1)	0.009	-0.007	0.045	0.061	0.041	0.047	0.051	0.087	0.058	0.042	0.046	0.036	0.053	0.089	0.054
	(0.063)	(0.063)	(0.063)	(0.061)	(0.063)	(0.074)	(0.060)	(0.056)	(0.063)	(0.062)	(0.065)	(0.063)	(0.065)	(0.060)	(0.066)
Innovation support$_{ci}$(PC1)	0.100	0.105*	0.099*	0.110*	0.089	0.098*	0.075	0.100*	0.102*	0.121*	0.125*	0.117*	0.100*	0.111*	0.083
	(0.062)	(0.058)	(0.059)	(0.060)	(0.060)	(0.058)	(0.048)	(0.060)	(0.059)	(0.066)	(0.065)	(0.066)	(0.059)	(0.062)	(0.058)
Regulatory burden$_{ci}$	-0.100**	-0.077	-0.090*	-0.075	-0.086	-0.098*	-0.064	-0.080	-0.109**	-0.088*	-0.080	-0.070	-0.099*	-0.063	-0.057
	(0.050)	(0.057)	(0.050)	(0.048)	(0.055)	(0.057)	(0.049)	(0.051)	(0.053)	(0.051)	(0.049)	(0.048)	(0.051)	(0.050)	(0.045)
DM * digital intensity$_{ci}$	0.214	-0.811*	-0.890**	-1.028**	-0.755*	-0.667	-0.831**	-1.066***	-0.968**	-0.825**	-0.590	-0.770**	-0.742*	-0.793*	-0.741*
	(0.648)	(0.414)	(0.449)	(0.413)	(0.412)	(0.414)	(0.406)	(0.381)	(0.414)	(0.413)	(0.399)	(0.391)	(0.409)	(0.416)	(0.419)
EPL$_{c}$* churn$_{ci}$	-0.579***	-0.538***	-0.540***	-0.425**	-0.665***	-0.506***	-0.550***	-0.447**	-0.529***	-0.506***	-0.569***	-0.665***	-0.565***	-0.571***	-0.439**
	(0.171)	(0.168)	(0.169)	(0.180)	(0.194)	(0.175)	(0.177)	(0.176)	(0.170)	(0.179)	(0.167)	(0.186)	(0.186)	(0.168)	(0.171)
Share age 25-49$_{ci}$	0.092**	0.102**	0.099**	0.083**	0.095**	0.115**	0.074**	0.097**	0.082**	0.098**	0.122***	0.094**	0.100**	0.108***	0.069*
	(0.039)	(0.041)	(0.039)	(0.039)	(0.041)	(0.045)	(0.035)	(0.040)	(0.040)	(0.045)	(0.044)	(0.042)	(0.043)	(0.041)	(0.040)
Constant	-0.468	-1.735***	-1.771***	-1.828***	-1.761***	-1.483***	-1.730***	-1.886***	-1.858***	-1.669***	-1.473***	-1.746***	-1.586***	-1.702***	-1.534***
	(0.631)	(0.494)	(0.528)	(0.479)	(0.489)	(0.494)	(0.465)	(0.454)	(0.483)	(0.485)	(0.475)	(0.459)	(0.486)	(0.491)	(0.481)
Observations	1,304	1,304	1,336	1,304	1,304	1,304	1,304	1,312	1,304	1,304	1,304	1,304	1,304	1,304	1,304
R-squared	0.613	0.624	0.616	0.604	0.615	0.629	0.633	0.599	0.618	0.611	0.623	0.622	0.606	0.624	0.623
Country FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Robust standard errors in parentheses (cluster: country*industry) ; *** p<0.01, ** p<0.05, * p<0.1

Table C12-b: Sensitivity to industry exclusion

(dependent variable: extensive AI adoption)

VARIABLES	(1) C10_C12	(2) C13_C15	(3) C16_C18	(4) C19	(5) C20	(6) C21	(7) C22_C23	(8) C24_C25	(9) C26	(10) C27	(11) C28	(12) C29_C30
Obstacle$_{cit}$ (PC1)	-0.140***	-0.141***	-0.138***	-0.095***	-0.137***	-0.154***	-0.139***	-0.138***	-0.147***	-0.143***	-0.140***	-0.144***
	(0.030)	(0.032)	(0.030)	(0.024)	(0.029)	(0.032)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.031)
Organisational capital$_{ci}$	0.181***	0.177***	0.180***	0.082*	0.164***	0.185***	0.180***	0.180***	0.223***	0.186***	0.180***	0.179***
	(0.041)	(0.041)	(0.041)	(0.060)	(0.043)	(0.041)	(0.040)	(0.040)	(0.032)	(0.041)	(0.040)	(0.041)
Train ICT$_{ci}$ (PC1)	0.195***	0.201***	0.202***	0.213***	0.166**	0.195***	0.201***	0.193***	0.189***	0.194***	0.195***	0.207***
	(0.064)	(0.064)	(0.064)	(0.059)	(0.067)	(0.064)	(0.064)	(0.064)	(0.063)	(0.064)	(0.064)	(0.068)
Digital access$_{ci}$ (PC1)	0.046	0.057	0.050	0.013	0.073	0.048	0.044	0.048	0.022	0.039	0.046	0.041
	(0.062)	(0.066)	(0.063)	(0.063)	(0.061)	(0.062)	(0.062)	(0.061)	(0.062)	(0.062)	(0.062)	(0.063)
Innovation support$_{ci}$(PC1)	0.100*	0.104*	0.100*	0.030	0.445**	0.102*	0.100*	0.103*	0.088	0.101*	0.103*	0.101*
	(0.058)	(0.058)	(0.058)	(0.026)	(0.181)	(0.059)	(0.058)	(0.058)	(0.059)	(0.058)	(0.058)	(0.058)
Regulatory burden$_{ci}$	-0.084	-0.107*	-0.084*	-0.020	-0.080	-0.080	-0.084*	-0.081*	-0.073	-0.081	-0.083*	-0.086*
	(0.052)	(0.055)	(0.050)	(0.040)	(0.049)	(0.051)	(0.050)	(0.049)	(0.048)	(0.050)	(0.049)	(0.050)
DM * digital intensity$_{ci}$	-0.790*	-0.767*	-0.790*	-0.744*	-0.779**	-0.784*	-0.785*	-0.825**	-0.753*	-0.788*	-0.802**	-0.790*
	(0.417)	(0.409)	(0.404)	(0.391)	(0.371)	(0.402)	(0.407)	(0.404)	(0.400)	(0.405)	(0.403)	(0.405)
EPL$_{c}$* churn$_{ci}$	-0.539***	-0.550***	-0.534***	-0.333**	-0.542***	-0.545***	-0.548***	-0.533***	-0.558***	-0.581***	-0.550***	-0.550***
	(0.173)	(0.170)	(0.171)	(0.130)	(0.164)	(0.170)	(0.173)	(0.172)	(0.174)	(0.178)	(0.173)	(0.176)
Share age 25-49$_{ci}$	0.095**	0.099**	0.095**	0.042**	0.094***	0.099**	0.094**	0.099**	0.098**	0.102**	0.097**	0.102**
	(0.040)	(0.041)	(0.041)	(0.021)	(0.035)	(0.041)	(0.040)	(0.042)	(0.040)	(0.042)	(0.041)	(0.046)
Constant	-0.582*	-1.613***	-1.654***	-1.527***	-1.588***	-1.654***	-1.665***	-1.708***	-1.663***	-1.717***	-1.701***	-1.676***
	(0.318)	(0.483)	(0.479)	(0.438)	(0.459)	(0.476)	(0.482)	(0.480)	(0.469)	(0.477)	(0.474)	(0.477)
Observations	1,340	1,340	1,340	1,340	1,340	1,340	1,340	1,340	1,340	1,340	1,340	1,340
R-squared	0.616	0.616	0.615	0.696	0.621	0.620	0.616	0.616	0.624	0.617	0.615	0.616

Robust standard errors in parentheses (cluster: country*industry) ; *** p<0.01, ** p<0.05, * p<0.1

Table C12-c: Sensitivity to industry exclusion

(dependent variable: extensive AI adoption)

VARIABLES	(13) C31_C33	(14) D	(15) E	(16) F	(17) G	(18) H	(19) I	(20) J58_J60	(21) J61	(22) J62_J63	(23) M	(24) N
Obstacle$_{cit}$ (PC1)	-0.137***	-0.135***	-0.136***	-0.139***	-0.136***	-0.138***	-0.139***	-0.117***	-0.124***	-0.115***	-0.129***	-0.135***
	(0.030)	(0.030)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
Organisational capital$_{ci}$	0.180***	0.179***	0.176***	0.179***	0.180***	0.179***	0.178***	0.183***	0.174***	0.179***	0.180***	0.181***
	(0.041)	(0.043)	(0.040)	(0.041)	(0.040)	(0.041)	(0.040)	(0.041)	(0.039)	(0.041)	(0.040)	(0.040)
Train ICT$_{ci}$ (PC1)	0.197***	0.222***	0.208***	0.180***	0.194***	0.187***	0.185***	0.117*	0.228***	0.212***	0.167**	0.193***
	(0.065)	(0.062)	(0.066)	(0.063)	(0.064)	(0.064)	(0.063)	(0.074)	(0.066)	(0.068)	(0.066)	(0.064)
Digital access$_{ci}$ (PC1)	0.048	0.014	0.067	0.048	0.049	0.052	0.054	0.056	0.093*	0.045	0.060	0.045
	(0.062)	(0.061)	(0.065)	(0.064)	(0.063)	(0.062)	(0.063)	(0.059)	(0.055)	(0.062)	(0.062)	(0.062)
Innovation support$_{ci}$(PC1)	0.099*	0.102*	0.100*	0.102*	0.101*	0.101*	0.104*	0.107*	0.102*	0.105*	0.101*	0.100*
	(0.058)	(0.059)	(0.058)	(0.058)	(0.058)	(0.058)	(0.058)	(0.058)	(0.058)	(0.059)	(0.058)	(0.058)
Regulatory burden$_{ci}$	-0.083*	-0.066	-0.086*	-0.083*	-0.092*	-0.084	-0.096*	-0.079	-0.091*	-0.066	-0.112**	-0.085*
	(0.049)	(0.050)	(0.050)	(0.049)	(0.053)	(0.052)	(0.050)	(0.050)	(0.049)	(0.050)	(0.054)	(0.051)
DM * digital intensity$_{ci}$	-0.766*	-0.695*	-0.825**	-0.728*	-0.790*	-0.777*	-0.823*	-0.863**	-0.777*	-0.627	-1.014**	-0.764*
	(0.405)	(0.409)	(0.400)	(0.411)	(0.408)	(0.404)	(0.423)	(0.415)	(0.449)	(0.478)	(0.429)	(0.408)
EPL$_{c}$* churn$_{ci}$	-0.541***	-0.597***	-0.520***	-0.647***	-0.540***	-0.544***	-0.609***	-0.444**	-0.515***	-0.461**	-0.536***	-0.610***
	(0.171)	(0.179)	(0.177)	(0.179)	(0.169)	(0.170)	(0.178)	(0.173)	(0.175)	(0.188)	(0.171)	(0.184)
Share age 25-49$_{ci}$	0.093**	0.097**	0.113***	0.093**	0.095**	0.099**	0.096**	0.101**	0.085**	0.096**	0.095**	0.096**
	(0.041)	(0.041)	(0.043)	(0.040)	(0.040)	(0.041)	(0.040)	(0.040)	(0.043)	(0.042)	(0.040)	(0.041)
Constant	-1.635***	-1.661***	-1.671***	-1.696***	-1.646***	-1.650***	-1.757***	-1.657***	-1.556***	-1.382**	-1.853***	-1.691***
	(0.479)	(0.479)	(0.475)	(0.485)	(0.484)	(0.478)	(0.498)	(0.485)	(0.524)	(0.547)	(0.498)	(0.481)
Observations	1,340	1,344	1,344	1,344	1,340	1,344	1,344	1,344	1,344	1,344	1,344	1,344
R-squared	0.615	0.626	0.619	0.618	0.614	0.617	0.618	0.597	0.609	0.567	0.610	0.616

Robust standard errors in parentheses (cluster: country*industry) ; *** p<0.01, ** p<0.05, * p<0.1

Table C14-a: Disaggregation of cost and personal obstacle variables

VARIABLES	No AI adoption (1)	PC1 AI adoption (2)	Extensive AI adoption (3)	No AI adoption (4)	PC1 AI adoption (5)	Extensive AI adoption (6)	No AI adoption (7)	PC1 AI adoption (8)	Extensive AI adoption (9)	No AI adoption (10)	PC1 AI adoption (11)	Extensive AI adoption (12)
High costs	0.068***	-0.076***	-0.079***									
(E_AI_BCST)	(0.023)	(0.027)	(0.024)									
Ethical concerns				0.081***	-0.073***	-0.074***						
(E_AI_BEC)				(0.021)	(0.025)	(0.021)						
Poor data protection							0.053*	-0.055	-0.090***			
(E_AI_BCDP)							(0.028)	(0.038)	(0.031)			
Legal uncertainty										0.098***	-0.089**	-0.106***
(E_AI_BLEG)										(0.027)	(0.036)	(0.030)
Organisational capital$_{ci}$	-0.068***	0.180***	0.172***	-0.075***	0.187***	0.179***	-0.075***	0.187***	0.181***	-0.079***	0.190***	0.183***
	(0.026)	(0.035)	(0.042)	(0.025)	(0.035)	(0.041)	(0.026)	(0.036)	(0.042)	(0.025)	(0.036)	(0.041)
Train ICT$_{ci}$ (PC1)	-0.259***	0.208***	0.186***	-0.262***	0.211***	0.188***	-0.263***	0.212***	0.192***	-0.260***	0.209***	0.186***
	(0.080)	(0.070)	(0.063)	(0.079)	(0.070)	(0.064)	(0.080)	(0.071)	(0.064)	(0.079)	(0.071)	(0.064)
Digital access$_{ci}$ (PC1)	-0.015	0.061	0.058	-0.005	0.051	0.048	-0.016	0.061	0.058	-0.008	0.054	0.050
	(0.075)	(0.070)	(0.060)	(0.071)	(0.068)	(0.058)	(0.074)	(0.069)	(0.061)	(0.073)	(0.069)	(0.059)
Innovation support$_{ci}$(PC1)	-0.002	0.101	0.109*	0.003	0.096	0.104*	0.004	0.095	0.103*	0.008	0.091	0.098*
	(0.040)	(0.078)	(0.061)	(0.038)	(0.076)	(0.060)	(0.039)	(0.076)	(0.060)	(0.038)	(0.075)	(0.058)
Regulatory burden$_{ci}$	0.022	-0.112**	-0.091*	0.009	-0.099**	-0.078	0.017	-0.105**	-0.085*	0.011	-0.100**	-0.078
	(0.049)	(0.052)	(0.051)	(0.046)	(0.048)	(0.048)	(0.050)	(0.052)	(0.051)	(0.048)	(0.050)	(0.049)
DM * digital intensity$_{ci}$	1.169***	-0.657*	-0.700*	1.260***	-0.754*	-0.800*	1.268***	-0.765*	-0.828**	1.305***	-0.796**	-0.853**
	(0.325)	(0.387)	(0.402)	(0.335)	(0.396)	(0.409)	(0.330)	(0.394)	(0.408)	(0.334)	(0.394)	(0.404)
EPL$_c$* churn$_{ci}$	0.270	-0.537***	-0.595***	0.278	-0.552***	-0.613***	0.285	-0.555***	-0.599***	0.257	-0.532***	-0.584***
	(0.178)	(0.187)	(0.186)	(0.171)	(0.181)	(0.176)	(0.179)	(0.183)	(0.176)	(0.172)	(0.174)	(0.168)
Share age 25-49$_{ci}$	-0.072**	0.103*	0.096**	-0.066**	0.098*	0.090**	-0.071**	0.102*	0.096**	-0.071**	0.102*	0.096**
	(0.034)	(0.054)	(0.041)	(0.034)	(0.052)	(0.040)	(0.034)	(0.054)	(0.040)	(0.033)	(0.053)	(0.039)
Constant	2.065***	-1.461***	-1.572***	2.227***	-1.635***	-1.752***	2.222***	-1.634***	-1.766***	2.263***	-1.668***	-1.796***
	(0.433)	(0.467)	(0.477)	(0.442)	(0.478)	(0.480)	(0.436)	(0.477)	(0.479)	(0.443)	(0.480)	(0.478)
Observations	1,400	1,400	1,400	1,400	1,400	1,400	1,400	1,400	1,400	1,400	1,400	1,400
R-squared	0.706	0.625	0.609	0.708	0.624	0.609	0.704	0.622	0.610	0.709	0.625	0.612

Robust standard errors in parentheses (cluster: country*industry)
*** p<0.01, ** p<0.05, * p<0.1

Table C14-b: Disaggregation of mismatch obstacle variables

VARIABLES	No AI adoption (1)	PC1 AI adoption (2)	Extensive AI adoption (3)	No AI adoption (4)	PC1 AI adoption (5)	Extensive AI adoption (6)	No AI adoption (7)	PC1 AI adoption (8)	Extensive AI adoption (9)	No AI adoption (10)	PC1 AI adoption (11)	Extensive AI adoption (12)
Incompatibility	0.098***	-0.105***	-0.118***									
(E_AI_BINC)	(0.023)	(0.031)	(0.029)									
Not useful				0.078***	-0.050**	-0.048						
(E_AI_BNU)				(0.022)	(0.025)	(0.029)						
Lack of expertise							0.087***	-0.114***	-0.130***			
(E_AI_BLE)							(0.029)	(0.040)	(0.033)			
Poor data availability										0.099***	-0.107***	-0.112***
(E_AI_BDDT)										(0.024)	(0.029)	(0.027)
Organisational capital$_{ci}$	-0.079***	0.192***	0.185***	-0.073***	0.185***	0.177***	-0.072***	0.185***	0.177***	-0.070***	0.182***	0.174***
	(0.025)	(0.036)	(0.041)	(0.026)	(0.036)	(0.043)	(0.026)	(0.035)	(0.041)	(0.025)	(0.034)	(0.040)
Train ICT$_{ci}$ (PC1)	-0.261***	0.210***	0.188***	-0.264***	0.211***	0.189***	-0.271***	0.222***	0.202***	-0.275***	0.224***	0.203***
	(0.079)	(0.071)	(0.065)	(0.080)	(0.072)	(0.066)	(0.080)	(0.070)	(0.063)	(0.080)	(0.071)	(0.065)
Digital access$_{ci}$ (PC1)	-0.007	0.052	0.048	-0.005	0.054	0.051	-0.013	0.058	0.055	-0.006	0.051	0.047
	(0.072)	(0.069)	(0.060)	(0.073)	(0.070)	(0.059)	(0.072)	(0.068)	(0.059)	(0.073)	(0.069)	(0.059)
Innovation support$_{ci}$(PC1)	0.005	0.093	0.101*	-0.003	0.100	0.108*	0.007	0.091	0.098*	0.007	0.091	0.099*
	(0.039)	(0.075)	(0.059)	(0.039)	(0.078)	(0.062)	(0.039)	(0.074)	(0.058)	(0.038)	(0.075)	(0.058)
Regulatory burden$_{ci}$	0.019	-0.108**	-0.087*	0.012	-0.102*	-0.081	0.016	-0.105**	-0.084*	0.018	-0.107**	-0.086*
	(0.048)	(0.051)	(0.050)	(0.050)	(0.052)	(0.052)	(0.048)	(0.049)	(0.048)	(0.047)	(0.050)	(0.049)
DM * digital intensity$_{ci}$	1.174***	-0.666*	-0.703*	1.236***	-0.734*	-0.780*	1.234***	-0.728*	-0.772*	1.277***	-0.777**	-0.824**
	(0.329)	(0.385)	(0.395)	(0.325)	(0.389)	(0.401)	(0.322)	(0.380)	(0.394)	(0.327)	(0.388)	(0.402)
EPL$_{c}$* churn$_{ci}$	0.233	-0.498***	-0.548***	0.348*	-0.606***	-0.665***	0.231	-0.478***	-0.523***	0.209	-0.471***	-0.527***
	(0.173)	(0.175)	(0.170)	(0.180)	(0.195)	(0.185)	(0.174)	(0.168)	(0.172)	(0.172)	(0.171)	(0.168)
Share age 25-49$_{ci}$	-0.069**	0.100*	0.093**	-0.070**	0.101*	0.094**	-0.070**	0.101*	0.094**	-0.069**	0.100*	0.093**
	(0.033)	(0.052)	(0.039)	(0.035)	(0.054)	(0.041)	(0.034)	(0.053)	(0.040)	(0.034)	(0.052)	(0.040)
Constant	2.045***	-1.444***	-1.540***	2.186***	-1.601***	-1.718***	2.127***	-1.516***	-1.619***	2.152***	-1.559***	-1.673***
	(0.440)	(0.464)	(0.465)	(0.428)	(0.470)	(0.475)	(0.433)	(0.457)	(0.463)	(0.437)	(0.469)	(0.473)
Observations	1,400	1,400	1,400	1,400	1,400	1,400	1,400	1,400	1,400	1,400	1,400	1,400
R-squared	0.710	0.628	0.615	0.708	0.622	0.606	0.707	0.628	0.615	0.709	0.628	0.613

Robust standard errors in parentheses (cluster: country*industry)
*** p<0.01, ** p<0.05, * p<0.1

Table C15-a: Age variable interacted with Eloundou model version indicator
(Eloundou et al., 2024 model version indicator)

VARIABLES	No AI adoption (1)	No AI adoption (2)	PC1 AI adoption (3)	PC1 AI adoption (4)	Extensive AI adoption (5)	Extensive AI adoption (6)
Share age 15-24$_{ci}$	0.220***		-0.245***		-0.223***	
	(0.057)		(0.079)		(0.076)	
Share age 50+$_{ci}$	0.139**		-0.251**		-0.206**	
	(0.066)		(0.124)		(0.084)	
Share age 15-24$_{ci}$*Eloundou m	-0.171***		0.204**		0.177**	
	(0.060)		(0.081)		(0.083)	
Share age 50+$_{ci}$*Eloundou m	-0.145**		0.243**		0.195**	
	(0.070)		(0.112)		(0.084)	
Share age 25-49$_{ci}$		-0.201***		0.306**		0.264***
		(0.072)		(0.126)		(0.096)
Share age 25-49$_{ci}$ *Eloundou m		0.509**		-0.796**		-0.660**
		(0.232)		(0.344)		(0.286)
Constant	1.324***	2.100***	-0.493	-1.487***	-0.761	-1.606***
	(0.489)	(0.454)	(0.605)	(0.498)	(0.588)	(0.483)
Observations	1,400	1,400	1,400	1,400	1,400	1,400
R-squared	0.713	0.713	0.631	0.633	0.618	0.619
Country FE	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes

Robust standard errors in parentheses (cluster: country*industry)
*** p<0.01, ** p<0.05, * p<0.1
All specifications include the full set of control variables.

Table C15-b: Age variable interacted with digital intensity indicator (Smiderle et al., 2026)

VARIABLES	No AI adoption (1)	No AI adoption (2)	PC1 AI adoption (3)	PC1 AI adoption (4)	Extensive AI adoption (5)	Extensive AI adoption (6)
Share age 15-24$_{ci}$	0.136***		-0.138***		-0.141***	
	(0.039)		(0.045)		(0.043)	
Share age 50+$_{ci}$	0.091*		-0.144*		-0.118*	
	(0.054)		(0.082)		(0.060)	
Share age 15-24$_{ci}$*smiderle	-0.097**		0.108**		0.111**	
	(0.044)		(0.052)		(0.055)	
Share age 50+$_{ci}$*smiderle	-0.114		0.146*		0.113	
	(0.080)		(0.088)		(0.078)	
Share age 25-49$_{ci}$		-0.133**		0.183**		0.163**
		(0.058)		(0.083)		(0.066)
Share age 25-49$_{ci}$ *smiderle		0.307		-0.399		-0.333
		(0.240)		(0.251)		(0.234)
Constant	1.495***	2.152***	-0.859	-1.566***	-1.021*	-1.671***
	(0.475)	(0.448)	(0.572)	(0.484)	(0.573)	(0.482)
Observations	1,400	1,400	1,400	1,400	1,400	1,400
R-squared	0.712	0.712	0.629	0.630	0.616	0.617
Country FE	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes

Robust standard errors in parentheses (cluster: country*industry)
*** p<0.01, ** p<0.05, * p<0.1
All specifications include the full set of control variables.

Note: The digital intensity indicator provides a sector-level measure of workforce digitalisation. Its construction begins with the occupational classification of each worker, as reported in the Labour Force Survey. Each occupation is assigned a digital skill intensity score, defined as the proportion of digital skills relative to the total set of skills required to perform the tasks associated with that occupation. This occupational-level measure was developed by Lennon et al. (2023); the reference provides further details on the methodology used to construct the indicator.

Occupational digital intensity scores are then aggregated to the sectoral level by computing a weighted average, with weights corresponding to the employment share of each occupation within the sector. The resulting sector-specific indicator thus captures both the digital skill requirements of occupational profiles and the composition of employment across occupations, providing a parsimonious and empirically grounded measure of workforce digitalisation.

Table C15-c: Age variable interacted with digital intensity indicator

(Calvino et al., 2018)

VARIABLES	No AI adoption (1)	No AI adoption (2)	PC1 AI adoption (3)	PC1 AI adoption (4)	Extensive AI adoption (5)	Extensive AI adoption (6)
Share age 15-24$_{ci}$	0.112***		-0.106**		-0.101***	
	(0.037)		(0.042)		(0.036)	
Share age 50+$_{ci}$	0.042		-0.120		-0.093	
	(0.050)		(0.095)		(0.063)	
Share age 15-24$_{ci}$*Calvino	-0.108***		0.102**		0.087**	
	(0.036)		(0.044)		(0.037)	
Share age 50+$_{ci}$*Calvino	-0.061		0.196		0.133	
	(0.095)		(0.171)		(0.118)	
Share age 25-49$_{ci}$		-0.098**		0.156*		0.138**
		(0.048)		(0.087)		(0.065)
Share age 25-49$_{ci}$ *Calvino		0.218		-0.435		-0.345
		(0.186)		(0.322)		(0.244)
Constant	1.738***	2.258***	-1.018*	-1.788***	-1.237**	-1.846***
	(0.430)	(0.469)	(0.520)	(0.539)	(0.501)	(0.518)
Observations	1,400	1,400	1,400	1,400	1,400	1,400
R-squared	0.713	0.712	0.630	0.631	0.616	0.617
Country FE	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes

Robust standard errors in parentheses (cluster: country*industry)
*** p<0.01, ** p<0.05, * p<0.1
All specifications include the full set of control variables.

Note: The digital intensity indicator is based on the taxonomy proposed by Calvino et al. (2018), which classifies sectors according to their degree of digitalisation. The indicator combines several sector-level measures, including the share of ICT investment (tangible and intangible), the share of intermediate ICT goods and services purchased, the stock of robots per 100 employees, the share of ICT specialists in total employment, and the share of turnover from online sales. Sectors are coded into four categories: 1 – highly digitalised, 2 – moderately highly digitalised, 3 – moderately low digitalised, and 4 – low digitalised.

For the purposes of this table, we construct a dummy variable equal to 1 if the sector is classified as highly or moderately highly digitalised (categories 1 and 2).

Table C16-a: Age variable interacted with job exposure to AI indicator (high job turnover)

High job turnover **(> median)** VARIABLES	No AI adoption (1)	No AI adoption (2)	PC1 AI adoption (3)	PC1 AI adoption (4)	Extensive AI adoption (5)	Extensive AI adoption (6)
Share age 15-24$_{ci}$	0.186***		-0.201***		-0.221***	
	(0.068)		(0.069)		(0.068)	
Share age 50+$_{ci}$	0.133***		-0.162***		-0.179***	
	(0.042)		(0.044)		(0.044)	
Share age 15-24$_{ci}$*Eloundou	-0.146**		0.152**		0.165**	
	(0.064)		(0.069)		(0.068)	
Share age 50+$_{ci}$*Eloundou	-0.111**		0.167***		0.185***	
	(0.053)		(0.058)		(0.054)	
Share age 25-49$_{ci}$		-0.223***		0.227***		0.247***
		(0.049)		(0.052)		(0.054)
Share age 25-49$_{ci}$ *Eloundou		0.359**		-0.505***		-0.559***
		(0.178)		(0.184)		(0.177)
Constant	0.672**	1.211***	0.011	-0.702**	0.085	-0.704**
	(0.332)	(0.310)	(0.342)	(0.341)	(0.315)	(0.335)
Observations	748	748	748	748	748	748
R-squared	0.824	0.826	0.813	0.812	0.756	0.755
Country FE	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes

Robust standard errors in parentheses (cluster: country*industry)
*** p<0.01, ** p<0.05, * p<0.1
All specifications include the full set of control variables.

Table C16-b: Age variable interacted with job exposure to AI indicator (low job turnover)

Low job turnover **(< median)** VARIABLES	No AI adoption (1)	No AI adoption (2)	PC1 AI adoption (3)	PC1 AI adoption (4)	Extensive AI adoption (5)	Extensive AI adoption (6)
Share age 15-24$_{ci}$	0.023		-0.190		-0.105	
	(0.223)		(0.263)		(0.197)	
Share age 50+$_{ci}$	0.078		-0.259		-0.194	
	(0.153)		(0.228)		(0.163)	
Share age 15-24$_{ci}$*Eloundou	0.137		0.081		-0.060	
	(0.370)		(0.416)		(0.334)	
Share age 50+$_{ci}$*Eloundou	-0.122		0.271		0.156	
	(0.249)		(0.306)		(0.239)	
Share age 25-49$_{ci}$		-0.105		0.332		0.275
		(0.158)		(0.242)		(0.176)
Share age 25-49$_{ci}$ *Eloundou		0.354		-1.078		-0.795
		(0.701)		(0.952)		(0.731)
Constant	3.243**	3.123**	-4.200**	-4.516**	-4.270**	-4.237**
	(1.609)	(1.395)	(1.888)	(1.897)	(1.791)	(1.703)
Observations	652	652	652	652	652	652
R-squared	0.564	0.564	0.446	0.448	0.467	0.468
Country FE	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes

Robust standard errors in parentheses (cluster: country*industry)
*** p<0.01, ** p<0.05, * p<0.1
All specifications include the full set of control variables.

Table C17: Age variable interacted with job exposure to AI indicator, results without sector G and I

VARIABLES	No AI adoption (1)	No AI adoption (2)	PC1 AI adoption (3)	PC1 AI adoption (4)	Extensive AI adoption (5)	Extensive AI adoption (6)
Share age 15-24$_{ci}$	0.243***		-0.278***		-0.294***	
	(0.087)		(0.086)		(0.081)	
Share age 50+$_{ci}$	0.120**		-0.209**		-0.192***	
	(0.055)		(0.089)		(0.062)	
Share age 15-24$_{ci}$*Eloundou	-0.226**		0.277***		0.289***	
	(0.096)		(0.102)		(0.100)	
Share age 50+$_{ci}$*Eloundou	-0.138**		0.216***		0.203***	
	(0.067)		(0.079)		(0.065)	
Share age 25-49$_{ci}$		-0.145**		0.251**		0.237***
		(0.064)		(0.098)		(0.076)
Share age 25-49$_{ci}$ *Eloundou		0.324		-0.641**		-0.611**
		(0.236)		(0.274)		(0.249)
Constant	1.526***	2.278***	-0.637	-1.508***	-0.719	-1.619***
	(0.520)	(0.452)	(0.604)	(0.518)	(0.599)	(0.512)
Observations	1,284	1,284	1,284	1,284	1,284	1,284
R-squared	0.709	0.708	0.628	0.628	0.618	0.618
Country FE	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes

Robust standard errors in parentheses (cluster: country*industry)
*** p<0.01, ** p<0.05, * p<0.1
All specifications include the full set of control variables.