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Human after all: Occupations at the core of AI adoption

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ABSTRACT

This paper investigates how firms' occupational structure shapes the adoption of artificial intelligence (AI) using matched administrative data on French firms and relying on an instrumental variable Probit model. We identify ICT engineers as the only occupational group with a robust and statistically significant effect on AI adoption. This finding holds for ICT and non-ICT Services sectors, and regardless of whether AI is developed in-house or acquired externally. Our estimates suggest that closing the occupational gap between adopters and non-adopters would require approximately 215,000 additional ICT engineers, and 45,000 for the firms most exposed to AI. The results highlight the critical importance of investing in advanced digital skills to support the broader diffusion of AI technologies.

1. Introduction

This paper investigates how the occupational structure of firms shapes their likelihood of adopting predictive artificial intelligence (AI), with a focus on occupations related to Information and Communication Technologies (ICT). Understanding this relationship is crucial given the transformative potential of digital technologies, particularly AI (Brynjolfsson et al., 2018; Agrawal et al., 2022), and the growing policy emphasis on promoting their diffusion as a driver of innovation and productivity (Goos and Savona, 2024). We contribute to this debate by offering the first firm-level analysis of how occupational composition influences AI adoption, conditional on other firm characteristics. Occupations provide a tractable and policy-relevant proxy for the capabilities embedded in firms, encompassing both digital infrastructure and skills (Cockburn et al., 2018; Tambe and Hitt, 2014). While occupational data are certainly an imperfect proxy for human capital, they nonetheless offer a useful lens to characterize workforce composition — particularly the availability of digital and technical expertise (see e.g. Harrigan et al., 2021). Our core hypothesis is that such skills constitute both a prerequisite for and a constraint on the diffusion of AI.

The empirical literature examining the relationship between AI and workforce characteristics has expanded rapidly in recent years. Most studies have focused on the labor market effects of AI, particularly its impact on job creation, destruction, and evolving skill requirements (Babina et al., 2023). However, findings on aggregate employment effects remain mixed, with little convergence across countries and empirical settings (see the contrasting results in Albanesi et al., 2024; Prytkova et al., 2024; Bonfiglioli et al., 2024; Acemoglu et al., 2022b).[1] On the demand side, firms active in ICT sectors, with greater cash reserves, higher R&D expenditures and STEM vacancies are more likely to express demand for AI-related skills (Alekseeva et al., 2021; Borgonovi et al., 2023; Draca et al., 2024). In contrast, comparatively little is known about how pre-existing human capital within firms facilitates the adoption of AI technologies. Evidence indicates that workforce skills explain a significant share of cross-country and cross-sector variation in AI uptake (Brey and van der Marel, 2024), and that ICT capabilities are positively associated with AI use at the firm level (Calvino and Fontanelli, 2023, 2024). Yet, the role of internal

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[1] Mixed results are common also in empirical studies on automation technologies (see also Jin and McElheran, 2018; Aghion et al., 2020; Domini et al., 2021, 2022; Bisio et al., 2025; Ughi and Mina, 2023).

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occupational structure – i.e., the distribution of functions and competencies within firms – remains largely unexplored, primarily due to a lack of detailed micro-level data.

To address this gap, we combine comprehensive official data sources from France – the 2019 ICT survey, linked employer–employee data (LEED), balance-sheets, and the business registry – to collect information on both the adoption of AI technologies and the occupational structure for a representative sample of approximately 9000 French firms in 2018. The ICT survey asks firms about their use of AI. We use this information to code a binary firm-level variable which informs on the adoption of AI and other digital technologies in 2018. This period is characterized by the early diffusion of AI, primarily centered on predictive analytics such as text mining and machine learning. Drawing on LEED and the detailed French occupational classification, we classify occupations in each firm by both qualification level and functional expertise. We focus on two macro-categories identified by the French classification: intellectual and intermediate occupations.[2] The former include occupations which are characterized by highly specialized technical knowledge or top managerial capabilities, while the latter include intermediate technicians and managers. Importantly, within these two macro occupational classes, we further distinguish between occupations related to information and communication technology (ICT), those which are not (non-ICT) and those which are not technical (e.g. managers). Our identification strategy relies on a two-stage IV Probit model, where 2018 occupational shares are instrumented with their 2011 values, a time when AI use by firms was highly unlikely (see also Babina et al., 2021).

Our findings show that one specific occupational group – ICT engineers – has a robust, positive, and significant effect on the probability of AI adoption. Other occupational shares, including managers and non-ICT technical staff, do not display a significant pattern. These results are confirmed by a series of robustness checks, all addressing the validity of our exclusion restriction that past values of occupational shares affect AI adoption through 2018 shares. We then explore the stability of the relationship across sectors. Results show that the effect of ICT engineers is concentrated in ICT and non-ICT Services sectors, where intangible processes and digital workflows are more prevalent. No significant effect emerges in Manufacturing, and Utilities & Construction. We also distinguish firms that acquire external AI solutions from those that develop their own AI systems. We find that ICT engineers are positively associated with both strategies, highlighting their role in enabling AI use regardless of the sourcing modality. Last, we quantify the ICT skill gap to approximately 215,000 additional full-time equivalent (FTE) ICT engineers, which amounts to more than half of France current stock. Focusing on firms most exposed to AI adoption, this gap amounts to approximately 45,000 ICT engineers. At current training rates, closing this gap would take almost a decade.

By providing micro-level insights into AI uptake, our paper bridges macro-level observations on skill-biased technological change with firm-level evidence on the demand for complementary human capital in the age of AI. First, our results align with the literature on skill-biased technological change: AI adoption is positively associated with the presence of ICT engineers, suggesting that the relevant capabilities are concentrated in highly skilled ICT occupations (Autor et al., 2003, 1998; Machin and Van Reenen, 1998). Second, we highlight the importance of advanced digital skills as key enablers of AI adoption. This supports the notion of complementarity between advanced ICT expertise and AI systems (Brynjolfsson et al., 2021). The exposure of high-skilled workers to AI (e.g., Webb, 2020; Felten et al., 2021) may thus reflect complementarity rather than substitution (Savona et al., 2022; Autor, 2024), particularly in the current phase of diffusion focused on predictive systems. This interpretation is also consistent with findings from recent studies on generative AI (see e.g. Noy and Zhang, 2023; Brynjolfsson et al., 2025; Felten et al., 2023). Third, our findings underscore the need for education and continuous training policies to expand the supply of ICT-related human capital. If the diffusion of AI is a policy priority due to its innovation and productivity potential, then addressing skill shortages through long-term investment in digital capabilities is essential.

The remainder of the paper is organized as follows. Section 2 describes the empirical strategy and discusses identification. Section 3 describes the data sources, while Section 4 presents results. Section 5 summarizes the key findings and discusses possible avenues for future research.

2. Empirical model

2.1. Basic setup

Our working hypothesis is that the probability that a firm adopts AI is a function of its occupational structure and of other relevant firm-specific characteristics. Our empirical model is as follows:

$$\Pr(\text{AI User}_i) = \Phi(\mathbf{S}_i, \textbf{Firm Characteristics}_i, \textbf{Digital Controls}_i, \textbf{Industry}_i, \textbf{Region}_i) \tag{1}$$

where $AIUser_i$ is the dummy variable indicating the use of AI by firm i in 2018. Vector **S** contains the shares of workers in the different intellectual and intermediate occupations focus of our study, as detailed in Section 3. It thus characterizes the occupational structure of a given firm; all other covariates control for other firm-specific characteristics influencing the probability of AI adoption and the characteristics of a firm's occupational structure.

Vector **Firm Characteristics** includes the logarithms of sales, age, physical capital, physical to intangible capital and physical capital to employment ratios, and export and multi-plant status. The inclusion of controls for age and size is warranted given that AI users tend to be larger and younger (Calvino and Fontanelli, 2023); these characteristics may also affect the occupational structure of firms. Conditioning estimates on the capital structure of the firm is necessary given that AI can be perceived as a combination of different tangible and intangible capital components (Corrado et al., 2021). Similarly, the multi-plant and export status dummies capture whether firms operate in multiple markets. The multi-plant variable also partly reflects whether a firm produces multiple goods or offers various services. In addition, a larger market size or access to diverse sources of data across various activities may encourage investment in AI technologies (see e.g. Alekseeva et al., 2021).

Vector **Digital Controls** accounts for the presence of complementary ICT technologies and activities within the firm, specifically Customer Relationship Management (CRM) systems, Enterprise Resource Planning (ERP) software and E-commerce. Digital infrastructure – internal or external to the firm – represents a pivotal enabler for the adoption of AI technologies (Calvino and Fontanelli, 2023; McElheran et al., 2023). On the one hand, a digital infrastructure – such as a fast broadband connection – enables firms to leverage the potential of various digital technologies, particularly cloud computing, which is crucial for the use of AI. On the other hand, the availability of meaningful, detailed datasets on productive inputs and consumers is instrumental for AI to enhance resource efficiency and commercial functions.

Lastly, vectors **Industry** and **Region** includes several fixed effects: **Industry** condition the estimates on the average characteristics of firms within industries, thereby accounting, among other things, for the fact that some sectors are more ICT or data-intensive; **Region** includes fixed effects specific to French administrative regions — controlling for spatial heterogeneity in technological ecosystems and infrastructure access, e.g., the existence of AI hubs in the surrounding of Paris, Lyon, Nice, and Grenoble areas.

[2] Notice that the label "intellectual" occupations is the translation of the French title of PCS 3: "Cadres et professions intellectuelles supérieures".

2.2. Addressing endogeneity

The use of occupational variables as predictors of AI adoption raises concerns about potential endogeneity, primarily due to simultaneity or reverse causality. Indeed, causation may run in both directions: while certain occupations may drive AI adoption through greater awareness of its potential, AI implementation itself may influence occupational structures, for instance by increasing the demand for ICT professionals (e.g. Felten et al., 2018, 2019, 2021; Babina et al., 2023). Moreover, forward-looking firms anticipating future AI adoption may begin hiring ICT engineers in advance, further blurring the direction of causality.

Given these concerns, we rely on an instrumental variable approach to estimate the causal impact of occupational structure on AI adoption. Since our dependent variable is a dummy variable, we estimate the following IV Probit model:

$$\begin{aligned}\text{AI User}_i^* &= \alpha + \mathbf{B_S}\hat{\mathbf{S}}_i + \mathbf{B_{X,2S}}\mathbf{X}_i + \epsilon_i \\ \mathbf{S}_i &= \gamma + \mathbf{B_Z}\mathbf{Z}_i + \mathbf{B_{X,1S}}\mathbf{X}_i + \omega_i \\ \text{AI User}_i &= \begin{cases} 1, & \text{if AI User}_i^* > 0 \\ 0, & \text{otherwise}\end{cases}\end{aligned} \tag{2}$$

Similarly to the Two Stage Least Square (TSLS) procedure, the IV Probit includes two steps. The first step estimates one regression for each endogenous variable included in **S** (defined in Eq. (1)), using vector **Z** as instrumental variables (one for each type of occupations) and **X**, the vector of controls **Firm Characteristics**, **Digital Controls**, **Industry** and **Region**. The second step follows the Probit specification of Eq. (1): the $AIUser$ dummy is the dependent variable, which is regressed on the predicted values of the first step ($\widehat{\mathbf{S}}$), and the vector of controls **X**. These two equations are jointly estimated via a Maximum Likelihood estimation procedure, allowing the use of sampling weights, by assuming that errors $\boldsymbol{\omega}_i$ and ϵ_i follow a multivariate normal distribution.

We instrument the vector of endogenous 2018 firm-level occupational shares using the 2011 firm-level shares. We argue that this choice is justified by the historical development of AI technologies: lacking precise information on the timing of AI adoption by each firm, we note that the diffusion of AI technologies by firms started after 2011 in the USA. This was due to many major advancements in AI systems, e.g., the development of the AlexNet neural network (Babina et al., 2021; Engberg et al., 2024).[3] Importantly, the United States led in early AI technology adoption; it is therefore plausible to assume that other countries, including France, followed with some time lag.

The 2011 occupational shares thus satisfy the two core conditions for instrument validity. First, they are relevant: past occupational composition is a strong predictor of a firm's current occupational composition. Second, conditional on the vector of controls **X**, they satisfy the exogeneity condition: in 2011, AI technologies were not yet widespread – particularly in Europe – reducing the likelihood that occupational shares were themselves influenced by AI adoption or anticipatory adjustments. This timing diminishes concerns over reverse causality or simultaneity bias and supports the plausibility of the exclusion restriction.

[3] After 2012, a significant acceleration in the development and application of deep learning and artificial neural networks took place, leading to substantial improvements in various AI-related tasks (see the discussion in Babina et al., 2021; Engberg et al., 2024; Agrawal et al., 2018). The use of deep learning and artificial neural networks began to surpass state-of-the-art non-AI related techniques in statistical analyses.

3. Data

3.1. Data sources and definitions of variables

We use four data sources: the 2019 French ICT survey, LEED, balance sheet data and the business register. These sources are matched relying on a unique firm identifier (the *Siren* code).

Our first data source is the 2019 ICT survey – administered by INSEE (French statistical office) – which provides information on firm-level AI use. The ICT survey features a rotating sample of approximately 9000 French firms operating in manufacturing, utilities, construction and non-financial market services. The sample is designed to be representative of firms with a workforce of 10 or more employees, while it includes all firms with more than 500 employees. These data offer an unprecedented level of granularity and representativeness in comparison to other commercial survey and allows an in-depth examination of AI adoption dynamics among the population of French firms with 10 or more people employed. In the 2019 ICT survey, AI is defined as follows: *"Artificial intelligence refers, under a single term, to the set of technologies aimed at performing, through computing, cognitive tasks traditionally carried out by humans: voice recognition, biometrics, image recognition, decision support, etc."*. With respect to AI, firms are asked the following question: *"In 2018, did your company make use of software and/or equipment incorporating artificial intelligence technologies?"*. We use the answers to this question to code the binary variable $AI\ User_i$, which takes the value of 1 for AI users and 0 otherwise. Note that the question is relative to 2018 – prior to the recent boom in generative AI – and thus informs on whether the firm was using AI systems aimed at performing data-driven out-of-sample predictions (e.g., forecasts and classifications) based on machine learning. Importantly, the survey also allows categorizing AI users into two distinct groups: AI buyers and AI developers. AI buyers refer to firms using AI technologies bought from external providers, while AI developers are firms employing AI systems developed in-house.

The ICT survey is designed to minimize concerns due to measurement error and self-reporting bias. First, the survey provides a clear definition of AI technologies, lowering the chances that firms may interpret differently the definition of AI or classify as AI other cutting-edge technology. Second, the survey is administered following Eurostat guidelines with respect to selecting a qualified respondent within the firm, thus reducing risks of overestimation/underestimation of AI use.[4] In this respect, Calvino and Fontanelli (2023) show that core patterns in AI adoption – such as firm size, sector, age, digital capabilities, and productivity – are remarkably consistent across countries. The robustness of these patterns underscores the reliability of the underlying data and provides strong evidence that respondents in the French ICT survey are well-informed and that the data accurately reflect firm-level AI use.

The ICT survey is also the source of data for the vector of **Digital Controls**. Information on the firm's broadband connection speed is used to build a binary variable proxying for the firm's digital infrastructure: this indicator is equal to one if fast if the firm has access to broadband connection equals or higher than 100 megabits per second, i.e., the highest speed among the possible available choices. Our rationale is that an efficient broadband connection enables firms to leverage the potential of various digital technologies – particularly

[4] According to Eurostat guidelines – followed by the French ICT survey – the respondent to the survey must be someone with key ICT responsibilities within the firm (such as the ICT manager or a senior ICT professional), or the managing director/owner in smaller enterprises. Importantly, the respondent should not be someone only responsible for accounting. Eurostat guidelines: https://ec.europa.eu/eurostat/cache/metadata/en/isoc_e_esms.htm#shortstat_popDisseminated; More info on respondent rules: https://circabc.europa.eu/ui/group/89577311-0f9b-4fc0-b8c2-2aaa7d3ccb91/library/1141554e-7c59-4dd0-84c4-6468b266dec1/details.

Table 1
Occupational classes defining the vector of shares of FTE occupations S_i.

	ICT	Technical non-ICT	Non-technical occupations
Intellectual occupations	ICT engineers	Non-ICT engineers	Non-technical (e.g., executives)
Intermediate occupations	ICT technicians	Non-ICT technicians	Non-technical (e.g., supervisors)

Notes: We report the level in blue and the type in red. ICT occupations include ICT engineers (PCS 388a, 388b, 388c, 388d and 388e) and ICT technicians (478a, 478b, 478c and 478d); technical non-ICT occupations include non-ICT engineers (PCS 38 excluding 388a, 388b, 388c, 388d and 388e) and non-ICT technicians (PCS 47 excluding 478a, 478b, 478c and 478d); non-technical workers include intellectual non-technical workers (PCS 3 excluding 38) and intermediate non-technical workers (PCS 4 excluding 47).

cloud computing – which are crucial for the use of AI (McElheran et al., 2023; Calvino and Fontanelli, 2023). Information on the use of CRM systems and ERP software and on participation in e-commerce activities are used to build binary indicators to condition the estimates on the existence of a digital infrastructure internal to firms. CRM systems and e-commerce practices allow the collection of customer and product information; ERP software favors the collection of data on productive inputs that can be leveraged to enhance resource efficiency through AI algorithms.[5] Business digital technologies like CRM, ERP, and e-commerce activities are arguably a good choice to proxy for digital capabilities in all sectors of the economy since they exhibit a lower likelihood of being linked to sector-specific attributes when contrasted with other advanced technologies, such as robots and 3D printers, which are considerably contingent on the sector (Calvino and Fontanelli, 2024).

Our second source of data are French LEED,[6] providing information on the population of French workers which we use to build the vector of occupation shares **S**. We aggregate employee-level data on hours worked and occupation type at the firm-level and compute the share FTE workers by occupation classes. Each share is defined as the total number of FTE in an occupation class over the total number of workers in the firm. Specifically, we include in the vector **S** the shares relative to Intellectual occupations (PCS 3) and Intermediate occupations (PCS 4), as defined by the French occupation classification PCS.[7] In the PCS, intellectual occupations are those requiring highly specialized technical knowledge, such as engineers and technical executives, along with employees performing managerial functions that demand in-depth scientific, administrative or commercial knowledge, whose tasks are typically difficult to routinize but also mostly exposed to AI (see e.g., Felten et al., 2021). Conversely, intermediate occupations encompass intermediate positions, between executives and execution agents (e.g., supervisors and foremen), and non-administrative technicians (e.g., appliance repairer, laboratory technicians). We further divide intellectual and intermediate occupations to distinguish between ICT, technical non-ICT and non-technical occupations, as illustrated in Table 1.[8] This classification thus reflects both the level and the type of workers' occupations.[9]

Our third and fourth data sources are balance sheets and the business register data[10] containing firm-level administrative data related to the set of **Firm Characteristics** on which we condition our estimates. Specifically, we control for firm sales and age, the ratio of physical to intangible capital, the ratio of physical capital to total FTE workers and the level of physical capital. All these variables are expressed in logs. We also control for the fact that firms may export or be multi-plant through the use of dummy variables.[11] All nominal variables are deflated using the SNA A38 industry specific price deflators provided by INSEE, the French National Statistical Office, with the exception of intangible capital, which is deflated using deflators from the EUKLEMS & INTANProd database (Bontadini et al., 2023). Last, vector **Industry** includes 1-digit NACE industries sourced from the ICT survey, while vector **Region** assigns each firm to an administrative region within France.

Importantly, we weight observations using the sample weights provided by the French ICT survey. The results discussed in next sections are therefore representative of the population of French firms with more than 10 employees.

3.2. Summary statistics

Table 2 shows the summary statistics of our entire sample and separately for the firms that used AI in 2018 and those that did not. In 2018, 11.01% of French firms were using AI. AI users are on average larger, in line with existing evidence (Acemoglu et al., 2022a; Zolas et al., 2020). Similarly, AI users have more than 2 times the physical capital of non-users. Approximately 35% and 37% of AI users export and own multiple plants, respectively, while the shares of exporters and multi-plant firms among non-users is around 31% and 32%. AI users also rely more on digital infrastructure, both within and outside the firm. The share of AI users leveraging fast broadband services (21.55%) is almost double the one of non-users (12.24%); AI users also adopt business digital technologies more frequently than non-users: rates of use of CRM, ERP and E-commerce among the former are 40.71%, 58.01% and 16.58% respectively, compared to 26.45%, 48% and 13.49% among the latter.

Importantly, we note that among AI users, 9.64% purchased AI from external sources, while 2.83% developed AI in-house, indicating that some firms both bought and developed AI. Notably, 51.42% of AI developers were also buyers, while only 15.08% of AI buyers were also developers. This points to a potential relationship between the decisions to buy and develop AI. It also suggests that firms may choose to leverage external AI capabilities even if they are capable of developing AI in-house, or that firms may leverage AI acquired from external providers to build their own AI systems.

Focusing on the occupational structure, AI users have a higher share of intellectual occupations with respect to non-AI users – 21,34% *vs.* 14,11% – and a lower one of manual workers — 32,83% *vs.* 41,79%.

[5] The ICT survey section that includes these variables is titled *"Electronic Data Sharing"* (the French translation for "Partage électronique d'information"), emphasizing their data-related role.

[6] Obtained from the *Déclaration annuelle de données sociales* (DADS). For more information at this link.

[7] For additional details on the PCS classification, version 2003, see this link https://www.insee.fr/fr/information/2497952 and Appendix B. The occupation is hierarchically structured. For instance, 4-digit classes starting with 3 (e.g., 388a) belongs to the PCS aggregate class 3.

[8] Classes 38 and 47, including engineers and technicians, correspond to the definition of techies used in Harrigan et al. (2021, 2023).

[9] Specifically, information on occupations are provided by the fourth level of the French classification of occupations, which offers detailed information on the type of occupation characterizing each worker employed by firms active in France. For instance, the category ICT engineers includes the following relevant categories of the French classification: PCS (388a, 388b, 388c, 388d and 388e). For further details, please refer to Section 3 and to Appendix B.

[10] For additional details about these datasets, please refer to this link for balance sheet data (FARE), and this link for the business register.

[11] We distinguish multi-plant firms based on information in the business register, which associates plants (*Siret* codes) with firms (*Siren* codes).

Table 2
Summary statistics.

	All firms	Non AI users	AI users
AI user	11,01%		
AI developer	2,83%		25,67%
AI buyer	9,64%		87,53%
Age	26,78	26,78	26,78
Sales (Thousands €)	14 741,25	12 827,71	30 204,52
Physical to intangible capital ratio	4,55	4,58	4,39
Physical capital to employment ratio	2,61	2,62	2,48
Physical capital (Thousands €)	3101,89	2779,89	5703,94
Multi plant	31,55%	31,10%	35,14%
Exporter	32,65%	32,09%	37,13%
Fast broadband	13,26%	12,24%	21,55%
CRM	28,02%	26,45%	40,71%
ERP	49,11%	48,00%	58,01%
E-commerce	13,83%	13,49%	16,58%
Share intellectual occupations (PCS 3)	14,91%	14,11%	21,34%
Share intermediate occupations (PCS 4)	16,32%	16,26%	16,82%
Share clerical occupations (PCS 5)	27,98%	27,85%	29,00%
Share manual occupations (PCS 6)	40,80%	41,79%	32,83%
Share ICT engineers (ICT of PCS 38)	1,95%	1,45%	6,04%
Share Non-ICT engineers (PCS 38 Excluding ICT)	4,20%	4,20%	4,17%
Share Non-Technical intellectual Occupations (PCS 3 Excl, 38)	8,75%	8,46%	11,13%
Share ICT technicians (ICT of PCS 47)	1,01%	0,93%	1,63%
Share Non-ICT technicians (PCS 47 Excluding ICT)	4,52%	4,58%	3,99%
Share Non-Technical intermediate occupations (PCS 4 Excl, 47)	10,79%	10,74%	11,19%

Notes: Weighted averages for the whole sample and distinguishing between AI users and other firms. Results for AI users, buyers and developers, exporter, multi plant, fast broadband, CRM, ERP and E-commerce are in terms of percentage of total firms. Estimation for occupation shares are the firm-level average share. Sales and physical capital are reported in terms of thousands of Euros.

The shares of workers in intermediate and clerical occupations are only slightly larger in AI users — 29% *vs.* 27,85%. Among intellectual occupations, AI users have higher shares of ICT engineers and non-technical occupations (6,04% *vs.* 1,45%), whereas the share of non-ICT engineers is approximately equal in users and non-users. Shares of intermediate occupations are very close across users and non users, also when disaggregated in ICT, non-ICT and non-technical occupations.

These patterns support the view that larger firms or ones with better digital capabilities are more likely to possess the complementary assets, which are necessary to adopt and generate value from AI technologies (Calvino and Fontanelli, 2023; McElheran et al., 2023). Furthermore, firms operating in larger, more complex, and diversified markets, as captured by multi-plant and export status, may be more inclined to adopt AI due the availability of richer datasets, which are critical for predictive AI applications. This evidence is also in line with our conjecture that occupational structures may also differ markedly across firms: AI users employ a higher proportion of ICT-related workers, particularly in intellectual occupations. Nonetheless, they may also rely on more basic ICT skills of intermediate-level technicians. For this reason, our empirical analysis focuses specifically on the shares of workers in intellectual and intermediate ICT occupations.

3.3. Testing for common trends in occupation shares

Before presenting our main results, we must examine the validity of a key identifying assumption. A central premise of our econometric strategy is that both adopters and non-adopters of AI follow a common trend in occupation shares prior to adoption. However, if AI adopters exhibit systematically (presumably) higher growth in ICT-related occupation shares prior to AI adoption, this would raise concerns about reverse causality. In such cases, firms may be adjusting their occupational structure in anticipation of adopting AI, thereby confounding the causal interpretation of ICT-related occupations enhancing the adoption of AI. To assess the validity of the common trend assumption, we estimate the following regression:

$$\mathbf{S}_{i,t} = \alpha + \sum_t \beta_t D_t + \beta_{AI} AI_i + \sum_t \beta_{t,AI} D_t \cdot AI_i + \epsilon_{it} \tag{3}$$

where $\mathbf{S}_{i,t}$ denotes of the vector occupational shares (e.g., ICT engineers) of firm i at time t, demeaned at the industry level; AI_i is a dummy equal to 1 if the firm reports using AI in 2018; and D_t are year fixed effects. Subscript t runs from 2010 to 2019. Year 2010 is the base year. For each year, the sample includes data for the full set of firms included of the 2018 sample used to estimate the IV probit model in Eq. (2). In this specification, the coefficients β_t capture a trend in occupation shares common to all firms, whereas the coefficients $\beta_{t,AI}$ capture differential trends in $\mathbf{S}_{i,t}$ for AI users relative to the common trend for each year. Significance in the coefficients $\beta_{t,AI}$ before 2018 would indicate different pre-trends between AI-users and other firms, raising concerns about reverse causality.

Estimated coefficients for $\beta_{t,AI}$ are presented in Fig. 1. The black vertical lines indicate the confidence intervals of the $\beta_{t,AI}$ coefficients when the dependent variable is the share of ICT engineers in firm employment. The gray dashed vertical lines represent the confidence intervals of the $\beta_{t,AI}$ coefficients when the dependent variable is the share of other occupations, which include non-ICT intellectual occupations and intermediate occupations. Firm employment also comprises clerical and manual workers. Results indicate that firms adopting AI in 2018 did not exhibit systematically different pre-trends in the share of ICT engineers and in the share of other occupations compared to non-adopters. This provides preliminary evidence against reverse causality as a potential concern in our econometric setting. Additionally, we find that AI adopters have higher occupation shares – by 3 percentage points for ICT engineers and 3.3 percentage points for other related occupation (see the estimates of β_{AI} in Table A.1 in Appendix A) –, suggesting that firms using AI are more likely to employ workforce profiles aligned with the set of occupations presented in Table 1. It is noteworthy that our instrument – shares in 2011 – does not exhibit a different trend between AI and non-AI users for that particular year.

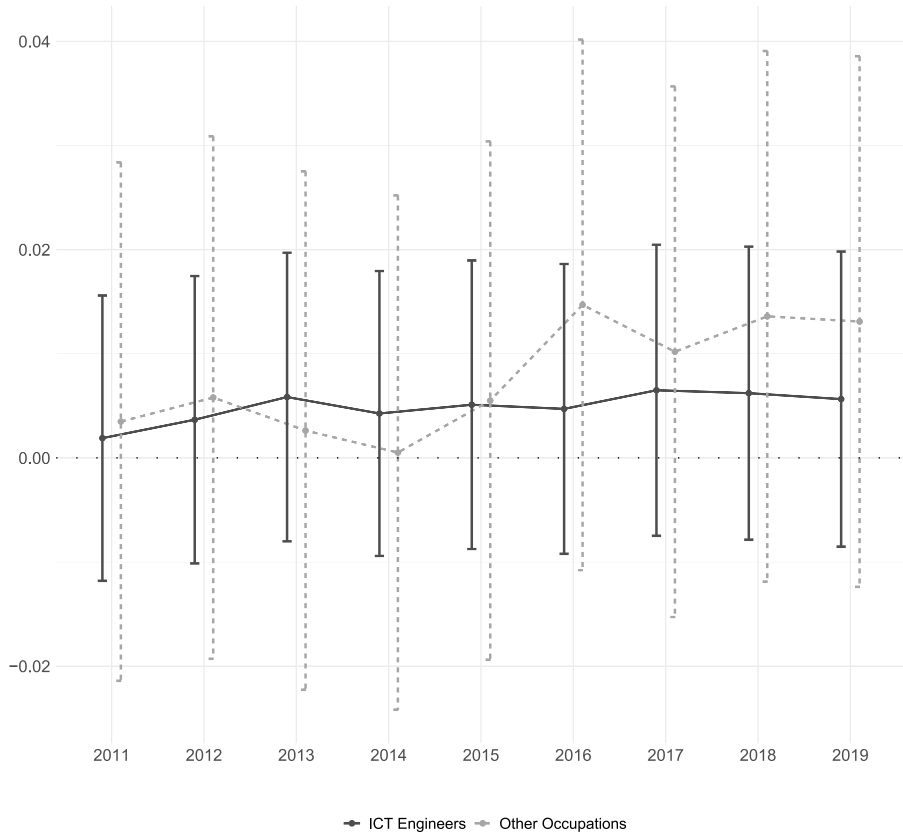

Fig. 1. The figure reports estimates of $\beta_{t,AI}$ coefficients of Eq. (3). Confidence intervals are at the 5% level, with standard errors clustered at the firm level. Estimated coefficients and their standard errors are reported in columns (2) and (5) of Table A.1, which also reports the full set of results of the estimation of Eq. (3). Year 2010 is the base year; each year includes information for all firms in our 2018 sample. The dependent variable 'ICT Engineers' is the share of ICT engineers over total employment in the firm; the dependent variable 'Other occupations' is the share of non-ICT intellectual occupations and intermediate occupations over total employment in the firm. Total employment also includes workers in clerical and manual occupations.

4. Occupational composition and AI use by firms

4.1. Baseline results

Table 3 shows the results of the estimation of the Probit (Eq. (1)) and IV Probit (Eq. (2)) models focusing on our variables of interest, namely the occupational shares. Columns (1) and (2) report the marginal effects of the Probit and the second stage equation of the IV Probit, whose dependent variable is the probability of using AI in year 2018.[12] Columns (3) through (8) show the first stages for the equations instrumenting the 2018 occupational shares with their 2011 values.[13]

Starting with columns (3) to (8), i.e. with the first-stage regressions, we observe that the diagonal coefficients in columns (2) through (7) of Table 3 are all positive and statistically significant. This confirms that each 2011 occupational share is a strong predictor of its corresponding instrumented 2018 share. In addition, several off-diagonal coefficients are also significant – some positive, others negative – indicating a complex pattern of interdependencies among occupational categories. These results suggest that certain occupations may act as complements (when coefficients are positive) or substitutes (when coefficients are negative) to others. For instance, the share of engineers other than ICT appears to be significantly and positively associated with non-technical intellectual occupational shares, while ICT engineers exhibit more limited positive correlations, underscoring their distinct role within firms.

Turning to column (2), which reports estimated marginal effects of the IV Probit second stage, the share of ICT engineers is positive and statistically significant, indicating that firms with higher shares of ICT engineers are more likely to adopt AI. In contrast, none of the other occupational categories emerge as significant predictors of AI adoption. This suggests that ICT engineers represent a pivotal occupational group in enabling or supporting the adoption of AI technologies within firms. Their distinct role stems from both their technical expertise in digital systems and data infrastructure, and their ability to interface between software systems and organizational processes. This unique combination of skills provides them with a unique position within firms to translate AI capabilities into operational value.

A comparison of the IV Probit results (column 2) with the results of the simple Probit (column 1) suggests the presence of a negligible positive bias affecting the coefficient of the share of ICT engineers. The direction of the bias is expected, as a self-reinforcing effect would artificially inflate the coefficient for ICT engineers. Yet, the difference between the two coefficients is negligible, and above all not statistically significant. This is in line with results presented in Fig. 1 pointing to the likely absence of reverse causality. Additional results reported in Table A.2 of Appendix A show that intangible assets, labor intensity, export activity, and multi-plant status are not significant predictors of AI adoption. This suggests that conventional firm-level characteristics related to scale, complexity, or investment in intangible capital do not, on their own, drive the decision to adopt AI (see also Calvino and Fontanelli, 2023). In contrast, the presence of fast broadband

[12] Marginal effects in a Probit model are computed as the sample average of: $\frac{\partial \Pr}{\partial x} = \frac{\mathrm{d} \Pr}{\mathrm{d} z}\frac{\partial z}{\partial x} = \phi(\hat{z})\hat{\beta}_x$, where $\phi(\cdot)$ is the standard normal density function.

[13] For completeness, Table A.2 in Appendix A shows the estimated coefficients for the full set of regressors.

Table 3
Probit and IV Probit — Marginal effects and first stages.

	(1) Probit	(2) IV Probit	(3)	(4)	(5)	(6)	(7)	(8)
		2nd Stage (t = 2018)	1st Stage (t = 2011)					
	Marginal effects	Marginal effects	ICT Eng.	Non-ICT Eng.	Other Int. Occ.	ICT Techn.	Non-ICT Techn.	Other Int. Occ.
ICT engineers (t)	0.168***	0.151***	0.808***	0.057***	0.005	0.005	−0.088***	−0.059***
	(0.041)	(0.055)	(0.040)	(0.018)	(0.016)	(0.015)	(0.023)	(0.016)
Non-ICT engineers (t)	−0.066	−0.007	−0.002	0.695***	0.104***	0.003	0.014	0.000
	(0.045)	(0.077)	(0.008)	(0.040)	(0.027)	(0.009)	(0.033)	(0.024)
Other intellectual Occ. (t)	−0.022	−0.067	−0.007	0.108***	0.694***	0.024**	−0.070***	−0.018
	(0.036)	(0.056)	(0.004)	(0.019)	(0.038)	(0.010)	(0.013)	(0.014)
ICT technicians (t)	−0.037	−0.143	0.046	0.040**	0.023	0.641***	−0.051**	0.002
	(0.078)	(0.103)	(0.034)	(0.020)	(0.018)	(0.060)	(0.023)	(0.024)
Non-ICT technicians (t)	−0.048	−0.088	0.021*	0.023*	−0.002	−0.003	0.606***	0.055***
	(0.044)	(0.071)	(0.012)	(0.013)	(0.012)	(0.006)	(0.026)	(0.020)
Other intermediate Occ. (t)	0.003	−0.010	−0.001	−0.005	0.010	0.002	0.069***	0.656***
	(0.032)	(0.048)	(0.004)	(0.007)	(0.006)	(0.003)	(0.012)	(0.023)
Observations	7427	7427	7427	7427	7427	7427	7427	7427
Pseudo R2	0.0453							
Log likelihood	−47 106.988	1 001 302.3						

Notes: Column (1) reports marginal effects derived from the coefficients of the Probit model, where the dependent variable is a binary indicator for AI use in 2018. Column (2) reports marginal effects derived from the coefficients of the second stage of the IV Probit model, whose dependent variable is a binary indicator for AI use in 2018. Columns (3) to (8) present results from the first-stage regressions, in which each occupational share in 2018 is instrumented with its corresponding value in 2011. All models include unreported coefficients including vectors of firms characteristics, controls for CRM and ERP software, engagement in e-commerce activities, and the presence of fast broadband as explanatory variables, whose marginal effects are reported in Table A.2. All industry fixed effects (at 1-digit level) and regional fixed effects are not reported for clarity. The model is estimated using survey weights. Standard errors of marginal effects in columns (1) and (2) in parenthesis are estimated by the delta method. Robust standard errors are reported in parentheses in columns (3)-(8). The reference category for occupational shares includes clerical and manual occupations. The complete version of this table is available in Table A.2.

* $p < 0.1$.

** $p < 0.05$.

*** $p < 0.01$.

and the use of complementary digital technologies – particularly ERP and CRM systems – are positively and significantly associated with AI adoption. These findings underscore the foundational role of digital infrastructure and technological maturity in enabling firms to transition toward AI. Fast broadband ensures the connectivity and data processing capabilities required for real-time applications, while ERP and CRM systems reflect a firm's prior experience in managing structured data and integrating digital tools into core business functions, both of which are likely prerequisites for successful AI implementation.

4.2. Robustness checks

The result of a significant association between the occupational share of ICT engineers and AI adoption may derive from underlying confounding factors rather than a causal link. To address this concern, we implement a series of robustness checks, all aiming to disentangle the observed relationship from alternative mechanisms and reinforce the validity of our identification strategy. Table 4 displays the results of these robustness checks.

We begin by estimating Eq. (2) using a TSLS approach within a linear probability model framework. This specification enables overidentification of the model and allows for conventional testing of instrument validity through overidentification tests, thereby providing a complementary assessment of the exclusion restriction. In a linear probability model, the OLS coefficient offers a direct interpretation as a marginal effect $\frac{\partial \Pr}{\partial x}$ and can thus be compared with the estimated marginal effect of the IV Probit coefficients. Results are displayed in column (1) of Table 4. First, the TSLS coefficient estimates remain significant and positive although larger than the ones estimated by the IV Probit (suggesting an important role for non-linearities better captured by the IV Probit). This reinforces the core result that ICT engineers are a key enabler of AI adoption. Notably, all other occupational categories, including non-ICT engineers and ICT technicians, are statistically insignificant or negative, suggesting that the positive effect is highly specific to ICT engineers. Second, the validity and the strength of the instruments are both confirmed. The Cragg–Donald statistic exceeds the conventional Stock–Yogo critical values for weak instrument diagnostics, indicating that the instruments used are highly relevant in the first stage. This is further validated by the Kleibergen–Paap rank statistics, which also exceeds commonly accepted thresholds (typically around 10). Together with the Hansen's J test, these diagnostics provide strong support for both the relevance and exogeneity of the instruments, satisfying the conditions required for a valid exclusion restriction. Altogether, the TSLS estimates lend further credibility to the chosen identification strategy and confirm the central role of ICT engineers in enabling AI adoption.

Furthermore, we conduct a series of additional robustness checks aimed at testing whether our results hold when focusing on specific sub-samples or when we exclude selected groups of firms.

First, we check whether our results stem from firms possessing greater endowments in automation technologies and production of automation-related assets. To empirically assess whether this alternative mechanism is at the basis of our results, we require detailed information on firms' endowments in automation-related capital or output. Standard census data on firm-level capital stocks, investments, and production lack the granularity needed to identify automation-specific assets and products. Instead, we rely on firm-level customs data, which report import and export transactions at the 8-digit Combined Nomenclature (CN) level, between 2003 and 2011. Drawing on the classifications proposed by Acemoglu and Restrepo (2021) and Bisio et al. (2025), we construct a proxy for automation-related capital and output by identifying firms that import and/or export automation-related machinery, equipment or products.

Based on this information, we estimate our baseline models for two specific groups of firms: those which neither import nor export automation-related machinery or products and those that both import and export such products. Results are in columns (2) and (3) of Table 4, respectively. If automation, rather than occupational structure, were

Table 4
Robustness checks for IV regressions of AI adoption on occupational shares. second stage marginal effects.

	(1) TSLS	(2) Automation goods	(3)	(4) Excluding the top 10% of	(5)	(6)	(7) Excluding
		Neither M/X	Both M/X	Labor Prod.	Sales	ICT Eng. Share	ICT sectors
ICT engineers (2018)	0.285***	0.166***	0.376**	0.146***	0.153***	0.148**	0.167*
	(0.093)	(0.060)	(0.160)	(0.057)	(0.055)	(0.075)	(0.087)
Non-ICT engineers (2018)	−0.005	−0.132	0.254	−0.011	−0.024	−0.016	0.001
	(0.086)	(0.112)	(0.183)	(0.085)	(0.081)	(0.081)	(0.078)
Other intellectual Occ. (2018)	−0.074	−0.064	0.016	−0.060	−0.067	−0.071	−0.044
	(0.064)	(0.063)	(0.153)	(0.062)	(0.057)	(0.059)	(0.061)
ICT technicians (2018)	−0.194*	−0.121	−0.121	−0.124	−0.142	−0.216**	−0.152
	(0.116)	(0.110)	(0.297)	(0.101)	(0.102)	(0.103)	(0.175)
Non-ICT technicians (2018)	−0.094	−0.081	0.038	−0.089	−0.084	−0.078	−0.081
	(0.066)	(0.080)	(0.210)	(0.074)	(0.072)	(0.071)	(0.071)
Other intermediate Occ. (2018)	−0.015	−0.014	0.141	−0.002	−0.009	−0.003	−0.015
	(0.048)	(0.049)	(0.224)	(0.049)	(0.048)	(0.048)	(0.048)
Observations	7427	5077	1306	6742	6746	6721	6708
Log likelihood		58 468.49	58 468.49	938 381.62	993 874.77	990 998.66	1 052 204.3
Adj. R^2	0.0118						
Cragg–Donald	270						
Kleibergen–Paap	29.88						
Hansen's Test	5.303						
P-value (Hansen's Test)	0.258						

Notes: Column (1) reports the estimated coefficient from the Two-Stage Least Squares regression, where the instruments are overidentified using specialized ICT engineers. Columns (2) to (7) report marginal effects derived from the coefficients of the second stage of the IV Probit model, with the dependent variable being a binary indicator for AI use in 2018. Results in column (2) are estimated on a sample of firms that neither import nor export automation goods. Column (3) presents results for firms that both import and export automation goods. Columns (4), (5), and (6) report estimates based on samples that exclude firms in the top 10% of the distribution of labor productivity (defined as the ratio of value added to the number of employees), sales, and the share of ICT engineers in 2011, respectively. Column (7) excludes firms operating in ICT sectors (NACE 2-digit sectors 26, 30, and 58–63). All models include unreported coefficients for firm characteristics, controls for CRM and ERP software use, engagement in e-commerce, and access to fast broadband as explanatory variables, whose marginal effects are reported in Table A.3. Industry fixed effects (at the 1-digit NACE level) and regional fixed effects are included but not reported for brevity. Robust standard errors are reported in parentheses in column (1). Standard errors of marginal effects in columns (2) to (7) are computed using the delta method. The reference category for occupational shares includes clerical and manual occupations. The reference category for occupational shares includes clerical and manual occupations. The complete version of this table is provided in Table A.3. First stage estimations are available upon request.
Standard errors in parentheses.
* denote significance at the 10% level.
** denote significance at the 5% level.
*** denote significance at the 1% level.

driving AI adoption, we would expect the effect of ICT engineers to disappear in at least one of these subsamples. Instead, across both groups, ICT engineers remain the only occupational category with a statistically significant effect, supporting the interpretation that their role in AI adoption operates independently of automation exposure. This strengthens the credibility of our exclusion restriction, which assumes that past occupational shares affect current AI use only through their impact on ICT-related capabilities.

Second, we check whether our results are driven by firms at the technological frontier. If our results were driven by frontier firms being systematically more likely to adopt AI due to unobserved advantages, the estimated effect of ICT engineers could reflect such latent drivers rather than a generalizable relationship. To this end, we estimate our baseline specification for three different subsamples of firms which systematically exclude firms belonging to the top 10% of the distribution in terms of labor productivity (column 4), firm size as proxied by sales (column 5), and ICT engineer intensity (column 6). Furthermore, we also exclude firms operating in the ICT-related sectors (column 7). These exercises are intended to test whether our results are disproportionately driven by a small group of large, highly productive, or ICT-intensive firms. Indeed, digital capabilities are known to play a key role in AI adoption (McElheran et al., 2023; Calvino and Fontanelli, 2024), with large and more productive firms typically being more digitalized and therefore systematically more likely to adopt AI technologies (Zolas et al., 2020; Calvino and Fontanelli, 2023; McElheran et al., 2023). Similarly, firms operating in ICT sectors are also more inclined to use AI (Calvino and Fontanelli, 2023) and account for two thirds of all ICT engineers in France. The persistence of the significance and positiveness of the coefficient on ICT engineers across columns (4) through (7) further supports the robustness of our findings. Estimated average marginal effects remain of the similar magnitude to those of the overall sample, even if we note a smaller p-value - 5.5% - in the case of column (7).

Taken together, all robustness exercises reinforce the validity of our identification strategy and the credibility of our exclusion restrictions. Across a wide range of alternative specifications — relating to the type of estimators, samples restriction targeting automation exposure, firm characteristics (productivity, size, endowments in ICT engineers and sectoral ICT characteristics), the share of ICT engineers repeatedly emerges as the only occupational feature significantly associated with AI adoption. We conclude that the relationship is driven by the general and pervasive role of ICT engineers as key enablers of AI adoption across the broader economy.

4.3. Heterogeneity across sectors and in AI use

We further enrich our baseline results in two ways. First, we test whether the relationship between ICT occupations and AI adoption is heterogeneous across macro-sectors. Second, we examine whether the relationship between ICT occupations and AI adoption differs based on how firms use AI.

The test of heterogeneity across macro-sectors is warranted because not all sectors are equally exposed to digital technologies, including AI (see e.g. Felten et al., 2021; Calvino et al., 2025). To this end, we modify our main IV Probit specification – Eq. (2) – by interacting the share of ICT engineers with macro-sectoral dummies. Specifically, we distinguish four sectoral categories: Manufacturing (NACE 10–33), ICT Services (NACE 58–63), Non-ICT Services (NACE 45–47, 49–56, 68,

Table 5
IV Probit — Marginal effects and First Stages with Sector-ICT Engineer Interactions.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Probit	IV Probit									
	(t = 2018)	2nd Stage (t = 2018)	1st Stage (t = 2011)								
	Marginal effects	Marginal effects	ICT Engineers in				Non-ICT Eng.	Other Intel. Occ.	ICT Techn.	Non-ICT Techn.	Other Inter. Occ.
			Manuf.	Util. & Constr	ICT Serv.	Non-ICT Serv.					
ICT engineers — Manufacturing (t)	0.206	0.177	0.574***	−0.001**	−0.013	−0.026**	0.461***	−0.125	0.057	0.427*	−0.133
	(0.245)	(0.479)	(0.081)	(0.001)	(0.010)	(0.011)	(0.157)	(0.097)	(0.046)	(0.250)	(0.092)
ICT engineers — Utilities & Constr. (t)	−2.636**	0.487	−0.001*	0.061***	−0.023***	−0.012*	0.209***	0.042	0.054***	0.264***	0.073**
	(1.165)	(4.377)	(0.001)	(0.005)	(0.006)	(0.006)	(0.045)	(0.033)	(0.013)	(0.043)	(0.031)
ICT engineers — ICT services (t)	0.192***	0.169***	0.000	0.000	0.827***	0.008*	0.021	−0.099***	0.010	−0.007	−0.047**
	(0.052)	(0.064)	(0.000)	(0.000)	(0.047)	(0.004)	(0.014)	(0.029)	(0.023)	(0.017)	(0.022)
ICT engineers — Non-ICT services (t)	0.204***	0.207**	−0.001***	−0.000**	−0.011***	0.860***	0.130***	0.012	−0.008	0.020	−0.065***
	(0.062)	(0.083)	(0.001)	(0.000)	(0.004)	(0.047)	(0.041)	(0.042)	(0.016)	(0.021)	(0.021)
Non-ICT engineers (t)	−0.027	0.023	0.005***	0.001*	−0.003	−0.003	0.718***	0.053*	0.004	0.121***	0.001
	(0.044)	(0.075)	(0.002)	(0.000)	(0.004)	(0.006)	(0.041)	(0.030)	(0.009)	(0.028)	(0.022)
Other higher intellectual Occ. (t)	0.018	−0.015	0.001	0.000	−0.005	0.028***	0.041***	0.650***	−0.002	0.013	0.073***
	(0.033)	(0.051)	(0.001)	(0.000)	(0.007)	(0.010)	(0.012)	(0.026)	(0.005)	(0.012)	(0.018)
ICT technicians (t)	−0.014	−0.126	0.003**	0.001**	0.013	0.035	0.039*	−0.040	0.643***	0.027	0.009
	(0.078)	(0.102)	(0.001)	(0.000)	(0.027)	(0.022)	(0.021)	(0.025)	(0.060)	(0.019)	(0.025)
Non-ICT technicians (t)	−0.020	−0.049	0.001	0.001*	−0.005***	−0.001	0.127***	−0.036***	0.025***	0.709***	−0.012
	(0.043)	(0.068)	(0.001)	(0.000)	(0.002)	(0.003)	(0.019)	(0.011)	(0.009)	(0.038)	(0.013)
Other intermediate Occ. (t)	0.015	−0.003	0.001*	0.000**	0.002	−0.002	−0.003	0.080***	0.003	0.014**	0.667***
	(0.031)	(0.047)	(0.000)	(0.000)	(0.003)	(0.002)	(0.006)	(0.012)	(0.003)	(0.006)	(0.022)
Observations	7427	7427	7427	7427	7427	7427	7427	7427	7427	7427	7427
Pseudo R2	0.0424										
Log likelihood	−47 250.086	2 497 907									

Notes: Column (1) reports marginal effects derived from the coefficients of the Probit model, where the dependent variable is a binary indicator for AI use in 2018. Column (2) reports marginal effects derived from the coefficients of the second stage of the IV Probit model, whose dependent variable is a binary indicator for AI use in 2018. Columns (3) to (11) present results from the first-stage regressions, in which each occupational share in 2018 is instrumented with its corresponding value in 2011. Columns (3) to (6) include first stage estimates for ICT engineers interaction, whereas columns (7) to (11) for other occupations. All models include unreported coefficients including vectors of firms characteristics, controls for CRM and ERP software, engagement in e-commerce activities, and the presence of fast broadband as explanatory variables, whose marginal effects are reported in Table A.4. All industry fixed effects (at 1-digit level) and regional fixed effects are not reported for clarity. The model is estimated using survey weights. Standard errors of marginal effects in columns (1) and (2) in parenthesis are estimated by the delta method. Robust standard errors are reported in parentheses in columns (3)–(11). The reference category for occupational shares includes clerical and manual occupations. The complete version of this table is available in Table A.4.

* $p < 0.1$.

** $p < 0.05$.

*** $p < 0.01$.

69–75, 77–82), and a residual group including Utilities & Construction. This aggregation strategy captures commonalities across more disaggregated sectors, balancing representativeness and sufficient variation in AI use within each group. The ICT engineers occupational shares are instrumented using its 2011 counterparts interacted with the sectoral dummies.

Results are reported in Table 5, which presents the Probit estimates in column (1) and the IV Probit estimates in columns (2) to (11). Column (2) reports the average marginal effects from the second stage of the IV Probit model. Columns (3) to (6) present the first-stage estimates for the interacted share of ICT engineers, while columns (7) to (11) report the first-stage estimates for all other occupational shares. These results reveal substantial heterogeneity across macro-sectors. The coefficient associated with the share of ICT engineers is positive and significant for both ICT and Non-ICT Services sectors. By contrast, they are not significantly different from zero in Manufacturing and Utilities & Construction.

The macro-sectoral findings underscore the context-dependency of AI adoption as a function of advanced ICT capabilities. Yet, our results are particularly relevant in the French context, where approximately 65% of firms with more than 10 employees operate in the services sector, accounting for two thirds of total value added. This means that a substantial majority of French firms belong to sectors where advanced ICT occupations are crucial for the adoption of AI technologies. In such sectors, the availability and deployment of advanced ICT skills are key enablers of AI diffusion.

We then examine whether the relationship between ICT occupations and AI adoption differs based on how firms use AI by distinguishing among firms that acquire external AI solutions (labeled as AI Buyers), those that develop their own internal AI algorithms (labeled as AI Developers). This exercise is motivated by recent empirical evidence showing that AI buyers and developers are different along several dimensions (Calvino and Fontanelli, 2024). AI developers tend to be younger and larger firms, differently from AI buyers. In terms of sectoral presence, AI developers are more likely to be found in the ICT sector, while AI buyers are more evenly distributed across industries. Finally, while both groups are generally more productive than non-AI users, only AI developers show a clear, significant productivity advantage even after accounting for firm characteristics, complementary assets and selection bias.

To account for such differences in AI use, we estimate the following bivariate Probit model:

$$
\begin{aligned}
\text{AI Buyer}_i &= \begin{cases} 1 & \text{if } \mathbf{B}_1\mathbf{X}_i + \varepsilon_{i,1} > 0, \\ 0 & \text{otherwise,} \end{cases} \\
\text{AI Developer}_i &= \begin{cases} 1 & \text{if } \mathbf{B}_2\mathbf{X}_i + \varepsilon_{i,2} > 0, \\ 0 & \text{otherwise,} \end{cases}
\end{aligned}
\tag{4}
$$

where vector $\mathbf{X}$ includes occupational shares $\mathbf{S}$, **Firm Characteristics**, **Digital Controls**, **Industry** and **Region**. Because firms can both purchase

Table 6
Bivariate probit results — Marginal effects.

	Bivariate probit		IV Bivariate probit	
	AI buyers (1)	AI develop. (2)	AI buyers (3)	AI develop. (4)
ICT engineers (2018)	0.090**	0.072***	0.095*	0.054***
	(0.038)	(0.016)	(0.053)	(0.021)
Non-ICT engineers (2018)	−0.145***	0.037**	−0.146***	0.027
	(0.045)	(0.017)	(0.045)	(0.017)
Other intellectual Occ. (2018)	−0.030	0.020	−0.031	0.008
	(0.034)	(0.016)	(0.034)	(0.016)
ICT technicians (2018)	−0.034	0.013	−0.037	0.002
	(0.081)	(0.022)	(0.081)	(0.023)
Non-ICT technicians (2018)	−0.052	0.016	−0.052	0.010
	(0.042)	(0.019)	(0.042)	(0.019)
Other intermediate Occ. (2018)	−0.002	0.001	−0.003	−0.006
	(0.031)	(0.016)	(0.031)	(0.016)
Observations	7427		7427	
Log Likelihood	−56 424.476		−56 621.593	
$\text{Corr}(\varepsilon_1;\ \varepsilon_2) = \rho$	.618		.619	

Notes: The dependent variables are the binary indicators for buying or developing AI in 2018. Columns (1) and (2) are marginal effects from the bivariate Probit model. Columns (3) and (4) use instrumented ICT engineers (2018) with their 2011 values. See Table A.5 for the full version. Standard errors of marginal effects in parentheses are estimated via the delta method. All models include unreported coefficients including vectors of firms characteristics, controls for CRM and ERP software, engagement in e-commerce activities, and the presence of fast broadband as explanatory variables, whose marginal effects are reported in Table A.5. All industry fixed effects (at 1-digit level) and regional fixed effects are not reported for clarity. The reference category for occupational shares includes clerical and manual occupations.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

external AI solutions and develop their own (see Table 2 and Hoffreumon et al., 2024), these two adoption modes may be jointly determined. Allowing for correlation between their error terms such that $\text{Corr}(\varepsilon_1;\ \varepsilon_2) = \rho$, the bivariate Probit model captures unobservable factors influencing these joint decisions to acquire external AI solutions and/or develop them in-house.

Table 6 reports the marginal effects of occupational shares on the probability of buying AI in column (1) and developing AI in column (2). In both cases, the marginal effects associated with the share of ICT engineers are positive and statistically significant, reinforcing the findings discussed in Section 4. This suggests that firms with a larger share of ICT engineers are more likely to engage with AI, whether by procuring it from external providers or by building it internally.

As an additional robustness check, Table 6 also reports results from experimenting an IV strategy in which the share of ICT engineers in 2018 is instrumented using its lagged value from 2011. Our objective is to isolate exogenous variation in ICT engineer shares, offering reassurance that our main results are not biased by endogeneity. The IV estimates are presented in columns (3) and (4). Note that we have found no prior art on bivariate Probit models with endogenous regressors. We then experimented with the estimation of a first step as described in Eq. (2) and inserted the predicted values of occupational shares in a regular bivariate model. Therefore, caution must be exercised when interpreting these results.

The positive association between ICT engineering intensity and AI adoption or development is confirmed for both AI buyers and developers, with qualitatively similar patterns. Furthermore, the marginal effect for non-ICT engineers is statistically significant in both equations, though it has opposite signs: negative for AI buyers and positive for AI developers. This highlights the differences in the set of skills required for AI: broader for development and more narrowly associated with ICT-specific implementation skills for the purchase of AI solutions. It also underscores the importance of workforce composition in shaping firms' AI strategies.[14]

4.4. Quantification

Our quantification exercise aims to estimate the gap of ICT engineers and assess how changes in their share within firms affect the probability of AI adoption. The process involves four steps:

1. *Estimating the difference in the ICT engineers' share.* We calculate the firm-level difference between the average sectoral share of ICT engineers among AI-using firms, denoted as $\bar{S}_{IE,\text{AI users}}$, and the firm-specific share of non-users, $\bar{S}_{IE,\text{Non-users}}$. This yields the firm-level difference $(\bar{S}_{IE,\text{AI users}} - \bar{S}_{IE,\text{Non-users}})$.
2. *Estimating the gap in ICT engineers' FTE.* We multiply the difference described in point 1 above by the firm-specific total headcount to estimate the firm-specific gap of ICT engineers in terms of FTE. We then sum firm-specific gaps over all observations to estimate the sectoral gap in ICT engineers.
3. *Estimating the impact on AI adoption.* Using the marginal effect of the ICT engineer share on the probability of adopting AI from Table 5, we compute the firm-level change in adoption probability as: $d\,\text{Pr} = \frac{\partial\,\text{Pr}}{\partial S_{IE}} \times (\bar{S}_{IE,\text{AI users}} - S_{IE,i})$.
4. *Aggregating the results.* Finally, we calculate the average change in the probability of AI adoption at the sectoral level in both absolute and relative terms.

This quantification exercise offers an estimate of the ICT workforce gap that would arise if non-AI users were to adopt the same occupational profile as current AI users. Our approach is a simplified one,

[14] Unreported results show that AI developers are typically younger firms, reflecting their proximity to the technological frontier and their active participation in entrepreneurial cultures that value rapid innovation and experimentation. See Table A.5 in Appendix A.

Table 7
A simple quantification exercise.

	All sectors	*Manuf.*[a]	*U. & C.*[a]	I. Serv.	NI. Serv.
Firm count	169,512	32,854	28,742	7177	100,739
Share of non AI users	88.72%	90.52%	91.99%	73.57%	88.30%
Share of AI users	11.28%	9.48%	8.01%	26.43%	11.70%
Number of ICT engineers in 2018	397,190	29,277	3,991	269,609	94,313
$\bar{S}_{IE,\text{Non-users}}$	1.62%	0.32%	0.05%	29.15%	0.86%
$\bar{S}_{IE,\text{AI users}}$	6.75%	0.54%	0.02%	48.47%	2.96%
Gap in ICT engineers	216,029	5531	201	115,205	95,092
Gap in ICT engineers for top 10%	44,520	1239	39	16,379	26,862
Initial probability	10.11%	8.96%	7.73%	17.46%	10.86%
Final probability	10.61%	9.10%	7.75%	24.89%	11.33%
Absolute change in probability	+0.51	+0.14	+0.01	+7.43	+0.46
Relative change in probability	4.36%	1.62%	0.18%	50.34%	4.44%

Notes: Manuf. stands for Manufacturing, U. & C. for Utilities & Constructions, I. Serv. for ICT services, and NI. Serv. for Non ICT Services. Reported statistics are based on the weighted sample of firms included in the ICT survey, amounting to 8537 firms. The top 10% represent non AI user firms with the highest initial probability of adopting AI. Statistics regarding probabilities are estimated using the marginal effects of the ICT engineer share from Table 5.

[a] Figures pertaining to Manufacturing and Utilities & Construction should be interpreted with caution due to the lack of statistical significance of the marginal effects reported in Table 5.

as we place the entire burden on ICT engineers, treating them as the central resource required for AI adoption. In doing so, we abstract from other potentially important determinants. First, our approach overlooks various factors that could influence AI adoption, such as differences in ICT-related capital endowments, firm size, etc. Second, from a longer-term perspective, one could assume a positive trend in the baseline probability of adoption, reflecting ongoing diffusion and the increasing accessibility of AI technologies to end users. Third, the exercise does not account for organizational heterogeneity in terms of digital maturity, sector-specific AI use cases, or the potential for task reallocation within firms that could mitigate the need for additional ICT specialists. Fourth, it ignores the potential impact of policy interventions, training initiatives, or labor market dynamics that might influence both AI adoption rates and the supply of ICT professionals. Acknowledging these limitations, our quantification exercise sheds light on the magnitude of the ICT engineer shortfall associated with the diffusion of AI (see Table 7).

The 2019 ICT survey, based on nearly 9000 respondent firms, represents approximately 170,000 firms in France with more than 10 employees. The vast majority of these firms (around 89%) do not use AI as of 2018, a proportion that remains relatively consistent across sectors — except in ICT Services, where AI adoption reaches 26%. French firms in our sample, representative for firms with more than 10 employees, counts around 400,000 ICT engineers in total. Although ICT Services are the smallest in terms of the number of firms (about 7000), it is by far the largest employer of ICT engineers, accounting for about two-thirds of the total. Non-ICT Services also employ nearly 100,000 ICT engineers. Unsurprisingly, ICT Services report the highest share of ICT engineers among its workforce, with a striking difference between non-AI users (29%) and AI users (48%). This pattern, consistent with our econometric results, is observed across all other sectors, with the exception of Utilities & Construction.

If non-AI users were to match AI users in the share of occupation, the resulting FTE gap would amount to 216,000 ICT engineers – equivalent to 54% of the ICT engineer workforce in our sample, with most of the additional demand concentrated in the services sectors. However, assuming that all firms would adopt AI in the short term is unrealistic. AI remains an evolving technology, and many of its potential applications are still under development. To provide a more plausible estimate, we instead focus on firms most exposed to AI adoption – defined as those within the top 10% of the predicted probability of adoption, but not using AI as of 2018. Under this scenario, the estimated shortfall in ICT engineers is significantly reduced to 45,000. According to official figures (Létroublon, 2024), current enrollment in engineering programs in France stands at around 155,000 students in the last three years of their academic programme, with a declining trend. The number of new engineering graduates in 2024 was around 55,000. Among the enrolled students, only 17,000 specialize in ICT-related fields, suggesting that France is likely to be currently producing 5500 (about 10% of its new engineering graduates) ICT engineers per year, a number well below the projected need, even under the more conservative scenario.

The average increase in the probability of AI adoption resulting from hiring ICT engineers is generally modest, amounting to just +0.51 percentage points — equivalent to a 4.4% increase in the likelihood of adoption. This mild effect is observed across nearly all sectors. The notable exception are ICT-related sectors, where the probability rises by 7.4 percentage points, corresponding to a 50% relative increase. At first glance, the overall effect of hiring additional ICT engineers may appear negligible. In our view, this reflects the early stage of AI adoption: although the technology is advancing rapidly, it remains in its infancy. The low adoption rate observed in the current analysis reflects the early phase of AI diffusion under scrutiny and suggests that we are still positioned on the flatter portion of the diffusion curve, with implications both probabilistic and economic. From a probabilistic perspective, marginal effects are inherently small when the base probability is low. Given that the unconditional probability of adoption in our sample is only 11%, the estimated marginal impact must remain limited. From an economic standpoint, this pattern aligns with the concept of sunk entry costs in emerging technologies. Early adopters often incur substantial initial investments to build the capacity required for AI implementation, which may yield limited immediate returns. However, as the technology matures and adoption costs decrease, the probability of adoption is expected to rise more sharply.[15]

Altogether, our quantification exercise suggests a significant mismatch between the observed supply of ICT engineers and the projected demand under broader predictive AI adoption scenarios. While the short-term effects of hiring ICT engineers on AI adoption remain modest, this reflects the early stage of diffusion and high initial entry costs. Notwithstanding the potential influence of the trends discussed above, demand for ICT skills is likely to intensify in the future. Bridging this gap will require sustained investment in education and training, along with targeted policies to support future adopters.

[15] A natural question arises as to why firms would willingly bear such high sunk costs. The answer lies in the pursuit of first-mover advantages, often sought by highly entrepreneurial firms.

5. Conclusion

This paper has estimated the impact of occupational composition – particularly with respect to ICT-related occupations – on firm-level adoption of artificial intelligence (AI). We have used rich data on a representative sample of French firms from the 2019 ICT survey, linked employer–employee data and balance sheet information, to estimate an IV Probit model. By doing so, we have provided compelling evidence on the enabling role of specific workforce profiles – namely ICT engineers – in shaping firms' propensity to adopt predictive AI technologies.

Our econometric analysis shows that the share of ICT engineers is the only occupational category with a consistently positive and statistically significant effect on the probability of AI adoption. This finding holds in the baseline IV Probit specification, which addresses potential endogeneity by instrumenting current occupational shares with their 2011 values. Robustness checks – including alternative estimation strategies (such as TSLS), overidentification tests, and sample restrictions based on exposure to automation or specific characteristics – reinforce the credibility of our identification strategy and of our result on the pivotal role of ICT engineers. The effect of ICT engineers is particularly pronounced in the ICT and non-ICT Services sectors and holds for both modes of AI integration, either by developing AI internally or by purchasing it. Altogether, this evidence points to the enabling role of ICT engineers being both broad-based and independent of the sourcing strategy adopted by firms. Our results are also broadly consistent with the insights offered by Babina et al. (2023) on the United States and studies on exposure of high-skilled occupations to AI (see e.g. Felten et al., 2021).

Our quantification exercise also reveals a substantial occupational gap between AI adopters and non-adopters: firms that did not adopt AI had significantly lower shares of ICT engineers. One could imagine to bridge the gap by aligning the ICT engineer share of non-user firms with the sectoral average observed among AI adopters. This would require approximately 215,000 additional full-time equivalent ICT engineers, representing more than half of the ICT engineers workforce in French firms with more than 10 employees. Importantly, the resulting increase in the average probability of AI adoption may appear modest. Yet, such small magnitudes are typical in the early stages of major technological transitions, particularly those that underpin the emergence of a new digital economy. Among the 10% of firms most exposed to AI, the required adjustment would amount to around 45,000 ICT engineers. These figures stand in stark contrast to the current annual increase of ICT engineers graduates in France, which amounts to approximately 5500.

Important implications for education and training policy emerge. In the period under investigation, the diffusion of AI was clearly constrained by shortages in advanced digital skills, particularly in ICT engineering roles. Bridging this human capital gap requires sustained investment in both higher education and continuous professional development. Expanding the pool of digitally skilled workers is essential not only to accelerate AI adoption but also to prevent the emergence of structural divides between firms and sectors with unequal access to critical technological resources. Ultimately, the evidence underscores a simple but critical insight: The adoption of AI is contingent upon the availability of advanced ICT expertise skills, and more broadly, advanced digital human capital.

While our study does not directly estimate the outcomes of AI adoption – such as gains in efficiency or profitability – it is reasonable to expect that the capacity to generate such returns extends beyond the act of adoption itself. If adopting AI requires the presence of ICT engineers, then effectively integrating AI into core operations is likely to depend on a broader set of skills. Successful AI deployment hinges not only on technical expertise, but also on complementary soft skills such as critical thinking, communication, and coordination, that ensure that AI systems are aligned with organizational objectives (see also Borgonovi et al., 2023). Future research should investigate how the interplay between technical and transversal skills shapes the performance effects of AI, and how firms can configure their workforce to fully harness the transformative potential of these technologies.

CRediT authorship contribution statement

Luca Fontanelli: Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Flavio Calvino:** Writing – original draft, Methodology, Conceptualization. **Chiara Criscuolo:** Writing – review & editing, Methodology, Conceptualization. **Lionel Nesta:** Writing – review & editing, Methodology, Conceptualization. **Elena Verdolini:** Writing – review & editing, Methodology, Funding acquisition, Conceptualization.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.labeco.2025.102754.

Data availability

The data that has been used is confidential.

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