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Digital Technologies, Hiring, Training, and Firm Outcomes: Evidence from AI and ICT Adoption in Indian Firms

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Abstract

In this study, using a novel dataset that matches firm-level data with online job vacancy data, we investigate the effects of firms' digital technology adoption on future hiring and the dynamics of hiring and training, focusing on different types of technologies and categories of occupations. First, we examine the impact of adopting different types of digital technologies, namely AI, Advanced ICT, and Basic ICT, on future firm hiring. Our findings reveal that less advanced digital jobs (eg. Basic ICT, Advanced ICT) are substituted by more advanced digital jobs (e.g. AI), while the advanced technology adoption by firms leads to increased overall hiring of non-digital roles. Second, we show that there is a positive relationship between training and new hiring only for one occupational category, namely, managers, with no significant relationship for other occupations. Third, we investigate the joint effect of training and technology adoption for firm performance. Our findings reveal that digital technology adoption enhances a firm's financial performance only when combined with internal staff training. The sole exception is AI, which yields positive performance benefits even in the absence of training.

Keywords

Digital Technology Adoption, AI, Hiring, Training, Online Job Vacancy Data, Firm Performance

JEL Codes: O33, O12, L20, D22

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1. Introduction

Technological progress has had an enormous effect on work, jobs, and skills, as well as employment throughout the history of mankind. One of the most impactful examples is the 19th century Industrial Revolution when machines replaced many professions that had previously required manual labor. This was a pivotal moment in human history and one that fundamentally changed modern society. The past decade has witnessed the emergence of advanced digital technologies, particularly those based on machine learning techniques, which have already begun to impact businesses (Agarwal et al., 2024). Technologies such as artificial intelligence (AI), cloud computing, and cybersecurity are evolving rapidly, sparking intense debates and significant concerns about their impact on employment.

The relationship between technology and employment has long been debated, particularly with the rise of automation through technologies such as robotics and artificial intelligence. While some studies suggest that new technologies may lead to job displacement (Frey and Osborne, 2017; Sheffi, 2024), others argue that they can create overall employment opportunities (Fiszbein et al., 2020; Kalyani et al., 2025; Domini et al., 2021). However, the effects of technology on employment are likely to depend on the type of technology and the nature of the occupation. This paper contributes to this debate by investigating the impact of various types of digital technology adoption on future firm hiring and how these effects vary across different occupational categories.

The primary domain of large-scale technology adoption is at the firm level. With the advent of new technologies, a good proxy to understand what a firm is currently doing or which technologies the firm is currently adopting is by looking at whom they are hiring. At the same time, firms might also choose to train existing staff to help with the adoption of new technologies. However, as noted by studies, a major issue faced in emerging economies is the lack of availability of skills. Therefore, to which extent firms adopt new technologies might rely on the supply of skills or the training of the existing workforce to adapt workers' skills to new labor processes or a combination of both. In this paper, we test whether there is a significant relationship between training and hiring. We also examine which strategy yields better outcomes for the firm: adopting new technology by hiring new employees, investing solely in training existing staff, or combining technology adoption through new hires with training the workforce.

Therefore, in this paper, we address the following research questions: *What is the impact of digital technology adoption on new hiring, and how does this impact vary across different digital technologies, such as AI, Advanced ICT, and Basic ICT? What is the relationship between training and hiring, and how do these relationships vary with different types of technology adoption and across various occupations? Which strategy leads to better performance outcomes for firms: technology adoption through hiring, training, or a combination of both?*

To address these research questions, we will exploit matched firm-level and online-job vacancy data on Indian firms. Following the growing literature, including studies by Rock (2019) and Acemoglu et al. (2022), we use the demand for digital technology-related skills, obtained from the text of online job posts descriptions, as a proxy for technology adoption. The basic premise of this approach is that, in the absence of detailed administrative data on firm-level technology adoption, we can, for example, infer the demand for AI by analyzing which firms are hiring machine learning engineers, deep learning specialists, and other related staff. We use a range of econometric techniques to deal with endogeneity and self-selection issues, including Instrumental Variable Approach and Propensity Score Matching.

We observe a clear substitution effect between more advanced and less advanced digital jobs, while advanced digital technology adoption leads to increased overall hiring for non-digital roles. Specifically, we observe that firms hiring for AI-related positions tend to reduce their demand for Advanced ICT (and Basic ICT) skills in the future, while AI adoption is related to an increase in non-digital hiring. Similarly, the adoption of Advanced ICT is associated with fewer future Basic ICT hires but a higher demand for non-digital roles. Regarding the relationship between training and hiring, we find a significant and positive relationship only for one high-skilled category—managers—where training is associated with increased new digital hiring. Furthermore, firms that adopt digital technologies and invest in staff training perform better than those that focus solely on hiring new workers.
The paper is organized as follows: After the introduction, section 2 provides the background to the research problem and a review of the existing literature. Section 3 presents the data and offers some descriptive evidence. Section 4 details on the determinants of technology adoption. Section 5 investigates the impact of digital technology adoption on future hirings. Section 6 discusses the relationship between hiring and training. Section 7 examines the effect of training and hiring on firm performance. Finally, Section 8 concludes the paper.

2. Background and related literature

Organizational capabilities are a significant driver of macroeconomic growth (Teece et al., 1997). The capabilities here refer to the “dynamic capabilities” that enable firms to “sense” opportunities or threats, “seize” them, and “adapt” by reconfiguring their resources to navigate an ever-evolving business landscape (Teece, 2007). In the current wave of digital transformation, adapting to a rapidly changing environment requires firms not only to identify which technologies to adopt but also to restructure their activities, production processes, and employment strategies. Past research has shown that a firm’s ability to adapt to new environments hinges on their human capital and absorptive capacity, defined as the ability to recognize, assimilate, and apply external knowledge for innovation and performance improvement (Cohen et al., 1990). Absorptive capacity of firms is very dependent on the skills and expertise of employees, for instance, studies have shown that high-skilled workers, for example, play a pivotal role in interpreting and implementing complex technologies (Cirillo et al., 2022; Autor, 2000; Bresnahan et al., 2002; Fabiani et al., 2005), and driving organizational transformation and innovation (Leiponen, 2005; Lundvall, 2009; B¨ockerman et al., 2012). Just as human capital is essential for adopting new technologies, the adoption of technologies, in turn, often leads to significant changes in a firm’s employment structure. Indeed, the question of how technology affects employment has been a longstanding and critical question with great academic and policy interest.

2.1 Technology and Employment

Studies have already shown that new digital technologies have restructured workplaces and led to changes in the relative demand of skilled workers and new competencies (Autor et al., 1998; Arnal et al., 2003; Bresnahan et al., 2002; Bartel et al., 2003), even though the results are mixed. The results are varied depending on the level of analysis (firm, region, sector), or the regions being analyzed or other aspects. Given that firm is the domain in which large scale technology adoption happens, in this study, this is the chosen level of analysis. On one side, digital technologies have been shown to boost productivity while displacing certain types of jobs (Brynjolfsson and McAfee, 2014; van Ark et al., 2008). For instance, it is estimated that up to 30% of jobs across various sectors could be automated by 2030 (Manyika et al., 2017), with robots and industrial automation contributing to job losses in manufacturing but simultaneously driving productivity gains (Acemoglu and Restrepo, 2018). Concerns about widespread technological unemployment remain as machines take over more human tasks (Acemoglu and Restrepo, 2020a). On the other hand, there is also contrasting evidence that technological adoption has created new employment opportunities, particularly in fields requiring advanced skills, such as AI development and software engineering (Autor et al., 2003; Bessen and Righi, 2020). Specifically, studies on robot adoption indicate that it has contributed to net job creation within adopting firms, although its broader market-level effects remain mixed (Koch et al., 2021; Acemoglu and Restrepo, 2020a; Domini et al., 2021).

Overall, the literature demonstrates that while technology adoption reshapes employment dynamics, its impacts are nuanced and depend on factors such as the type of technology, the industry, the geographical location, etc. This is exactly what we tackle in this paper. In the first part of the paper, we investigate how heterogeneous the effects of digital technology adoption on employment are across different occupations and across different technologies.

2.2 Technology adoption and investments in human capital

The relationship between technology and employment is primarily influenced by how organizations change with technology adoption, the availability of skills both within and outside the organization, and the strategies firms employ, be it hiring new employees, training existing staff, or a combination of both. Firms may face trade-offs between these approaches, as shifting the workforce composition by hiring employees with specific skills (Acemoglu, 2002; Link and Siegel, 2003) might, in some cases, yield higher returns than allocating resources to on-the-job training. However, studies have argued that upgrading employees’ skills is beneficial for firms while adopting new technologies (Boothby et al., 2010). Most of the time, even if the required new skills are not readily available within the firm, they must be seamlessly integrated into the firm’s workflows and contextual production processes (Boothby et al., 2010). As a result, the combination of skills required is often largely firm-specific, as evidenced by the work of De Marzo et al. (2023). The more firm-specific these skills are, the more efficient it may be to train existing employees rather than hire externally (Osterman, 1995). As past studies have argued, during the complex process of adoption of radical new technologies, training could play an important role in shaping worker’s perception of technology and openness to related organizational changes (Ouadahi, 2008).

Studies have also suggested that, while firms may invest in training, the extent of such investments could vary significantly across different occupations. Lepak and Snell (2002) following the resource-based approach argues that, since the required skills are often specific to firm activities, firms may find it sufficient to prioritize training for a small number of roles that require firm-specific expertise and advanced human capital. Additionally, companies may limit training to these key roles due to the challenges of evaluating their financial benefits (Berge, 2008; Guerci et al., 2010) or because they favor acquiring external talent to bring in new competencies, the reason being the lengthy, uncertain, and risky nature of internal skill development programs (Kor and Leblebici, 2005; Sirmon et al., 2007). Even though there are plausible interpretations on why firms invest in training and why this could differ even internally within firms, no studies provide fine-grained evidence on how firms do on-the-job training to enrich their competencies and which kind of human capital they focus on. This could be due to the lack of data which we also face in the current study. Nevertheless, in this direction, we check the relationship between training and hiring of different kinds of occupations.

2.3 Technology adoption, investments in human capital and firm performance

Looking at the theory and evidence, it is reasonable to assume that firms benefit from on-the-job training, although the specific advantages may be less clear. However, there are also arguments for why firms might prefer external hiring rather than internal training, particularly while adopting new technologies that come together with organizational changes. Human capital theory (Becker, 1964) suggests that investing in employee training and education typically generates economic value by increasing their knowledge and skill levels, which in turn boosts their productivity. According to Becker (1964), such investments are not necessarily anticipated to enhance a firm's financial performance. Similarly, other studies have raised doubts about the financial returns of human capital investments, finding the relationship to be ambiguous or context-dependent (Almeida and Carneiro, 2009; Bartel, 2000; Frank and Obloj, 2014; Jones et al., 2012). For instance, research has shown that internal training enhances performance growth only when coupled with the implementation of new processes or product technologies (Maliranta and Asplund, 2007). From a standard human capital theory perspective, one could argue that on-the-job training might simply lead to higher wages in competitive labor markets, where other firms also provide training, making it difficult for the investing firm to capture the returns. This is especially true for "perfectly general" training. Here, we argue that, in most cases, firms have little reason to provide "perfectly general" training, since, as such training can be offered by external institutions. When firms engage in on-the-job training, very likely it is highly organizational-specific. Moreover, as discussed earlier, during periods of organizational change, it becomes crucial for several reasons—such as integrating complex knowledge into specific production processes, shaping employee perceptions of new technologies—to train existing employees, which could yield positive financial outcomes for firms. In this study, we analyze the joint effect of on-the-job training and technology adoption on firm performance.

3. Data Description

In this study, we use and merge two datasets, i) the online job vacancy data and ii) firm-level balance sheet data.

3.1 Online job vacancy data

General data features: Our first data source is online job vacancies posted on Naukri.com, India's leading recruitment platform since its establishment in 1997. The platform serves corporate recruiters, placement agencies, and job seekers. The data, collected through web scraping, span the years 2016, 2017, 2019, and 2020, resulting in a sample size of approximately 20 million vacancies after removing duplicates. Each vacancy includes raw text detailing various job characteristics based on free descriptions. The observations are organized into distinct fields such as job title, a comprehensive free-text job description with sub-fields "Role" and "Role Category" (roughly similar to ISCO-08 2-digit and 4-digit occupational codes, respectively), and "Education" (detailing required educational qualifications). Additionally, for each vacancy, we collect information on the industry, company name, posting date, workplace location, required experience and skills, and the pay rate, if disclosed by the company. Individual job posts are classified into occupational categories following De Marzo et al. (2023). They use machine-learning techniques to map job titles to their corresponding ISCO-08 occupational codes at the 2-digit level.[1]

1 The data operations to classify occupations from the online job data is described in De Marzo et al. (2023).

Construction of digital technology adoption variables: We create the adoption variables in line with Acemoglu and Restrepo (2020b) and Stapleton et al. (2021), who used demand for skills by firms to proxy adoption of technologies. We use online job posts by firms to proxy the adoption of different digital technologies by firms. To match job posts to specific digital technologies, we adopt the keywords from Sostero and Tolan (2022). In particular, we focus on AI, Advanced ICT and Basic ICT. For each job post, we determine whether or not its text contains any keyword related to one of these digital technologies. We then associate to each firm the number of job posts containing at least one keyword for each of the three categories we consider.

3.2 Firm-level Data

As mentioned above, to study digital technology adoption and hiring of firms in the Indian labor market, we match our vacancy data with detailed firm-level information from the Prowess database, gathered by the Centre For Monitoring Indian Economy (CMIE), a private company providing information on Indian firms. The information is collected by CMIE from firms' annual balance sheets and income statements, and covers both publicly listed and non-publicly traded firms from a wide cross-section of manufacturing, services, utilities, and financial industries. These companies account for around 70 per cent of India's industrial output, 75 per cent of corporate taxes, and more than 95 per cent of excise taxes collected by the Indian Government. Prowess is considered the largest firm-level database for India, has allowed researchers to track several dimensions of firm characteristics over time (Goldberg et al., 2010), and has been employed in different studies to investigate firm dynamics and production activities (Coad et al., 2021; Goldberg et al., 2010; Dosi et al., 2017). Hence, Prowess allows us to observe rich information on the firms posting online vacancies, and to connect the nature of skills they demand to firm characteristics and performance, such as, their growth, profitability, size, age, R&D investments, wages and export status. The list of all the variables we exploit in the empirical analysis, along with their definitions and summary statistics, are presented in Table 1.

As reported in De Marzo et al. (2023), the Naukri-Prowess matched dataset comprises 1,556,394 job ads from 5,237 firms across 209 cities. Among these vacancies, 25% are for managers, 39% for professionals, 20% for technicians, 9% for clerical support workers, and 8% for service and sales workers, while craft workers, machine operators, and assemblers account for only a small fraction. The descriptives reported below are for the matched sample.

3.3 Descriptives

In Figure 1, we observe the share of firms adopting digital technologies relative to the total number of firms in 2019. This figure exclusively represents digital technology adopters. Specifically, nearly 13 percent of all firms are adopting AI technologies, while over 9 percent of firms are engaged in advanced ICT and basic ICT adoption. These percentages highlight the varying degrees of technological adoptions across firms, with AI adoption representing the most significant share.

In Figure 2, the distribution of digital technology adopters across firm age categories[2] is presented for the year 2019. The highest share of AI adopters is observed among younger firms, particularly those less than 15 years old and those between 15-21 years old, with approximately 16% and 18% adoption rates, respectively. For advanced ICT and basic ICT technologies, no significant variation is noted across age categories, with adoption rates remaining relatively consistent regardless of firm age.

In Figure 3, the share of digital technology adopters is shown across firm size categories[3] in 2019. Here, larger firms demonstrate a higher propensity for adopting digital technologies compared to smaller firms, indicating that firm size may be a significant factor in the likelihood of technology adoption.

Figures 4, 5, and 6 illustrate the share of digital technology adopters across various NIC 2-digit sectors for AI, Advanced ICT, and Basic ICT, respectively for 2019. In Figure 4, AI adoption is particularly high in sectors such as Administrative Support Services, Professional, Scientific, and Technical Activities, Transportation and Storage, and IT & Communication.

2 Age category based on quantiles of the firm's age variable.

3 Size category based on quantiles of the firm's Sales variable.

In Figure 5, advanced ICT adoption is most prominent in sectors like Arts, Entertainment and Recreation, Transportation and Storage, and IT & Communication. Finally, Figure 6 shows a significantly higher share of basic ICT adoption in the Arts, Entertainment, and Recreation sector, while the remaining sectors exhibit a relatively uniform level of adoption. The two-digit sector classification is provided in the footnote.[4]

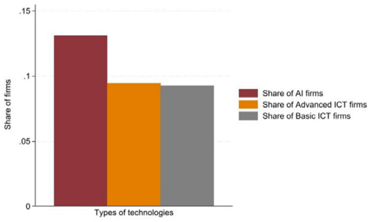

Figure 1: Share of different digital technology adopters in 2019.

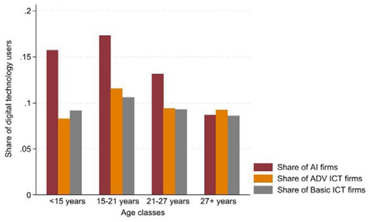

Figure 2: Share of different digital technology adopters by age classes.

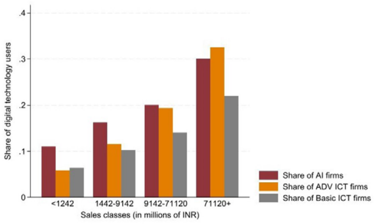

Figure 3: Adoption of digital technologies by firm size.

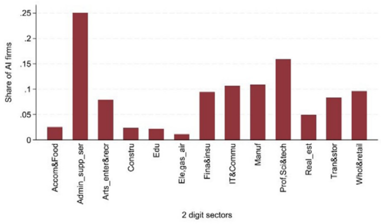

Figure 4: Share of AI technology adopters across NIC 2-digit sectors.

Variables	Definition	Mean	Median	SD
Sales (in INR)	Total sales from industrial goods	16878.985	1850.300	136348.068
R&D intensity	R&D expenditure over total sales of the firm	0.004	0.000	0.041
Export intensity	Export expenditure over total sales of the firm	0.052	0.000	0.174
Software intensity	Software expenditure over total sales of the firm	0.006	0.000	0.202
Firm growth	Log difference in sales between t & t-1	0.099	-8.457	8.806
Staff training intensity	Staff expenditure over total sales of the firm	0.040	0.003	1.054
AI Adoption	Takes value 1 if the firm adopted AI technologies	0.082	0.000	0.274
Advanced ICT Adoption	Takes value 1 if the firm adopted Advanced ICT technologies	0.069	0.000	0.253
Basic ICT Adoption	Takes value 1 if the firm adopted Basic ICT technologies	0.059	0.000	0.235

Table 1: Descriptive Statistics

4 Explanation of 2 digit sector abbreviations: Ele,gas air - Electricity, gas, air conditioning supply; Water,waste magt - Water supply, waste management; Constru - Construction; Whol&retail - Wholesale, retail trade; Tran&stor - Transportation, storage; IT&Commu - Information, communication; Accom&Food - Accommodation, food service; Fina&insu - Financial, insurance activities; Real est - Real estate activities; Prof,Sci&tech - Professional, scientific, technical activities; Admin supp ser - Administrative, support service activities; Pub admin&def - Public administration, defence; Edu - Education; Health&soci work - Human health, social work activities; Arts enter&recr - Arts, entertainment, recreation; Others - Other service activities; Acti households - Activities of households;

India presents an ideal setting for this study due to its widespread adoption of IT and advanced digital technologies, alongside a robust pool of technological talent. Compared to many other countries, India's strong IT sector and skilled workforce provide a unique opportunity to examine the employment effects of AI and advanced ICT adoption.

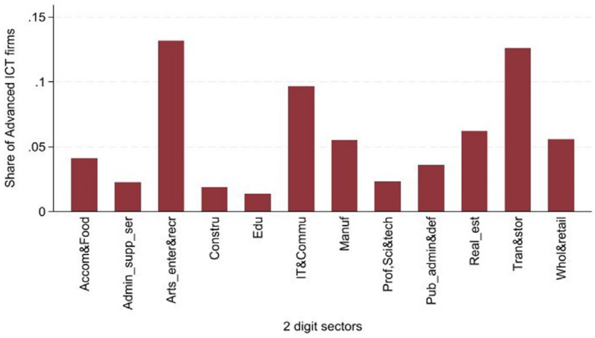

Figure 5: Share of Advanced ICT adopters across NIC 2-digit sectors.

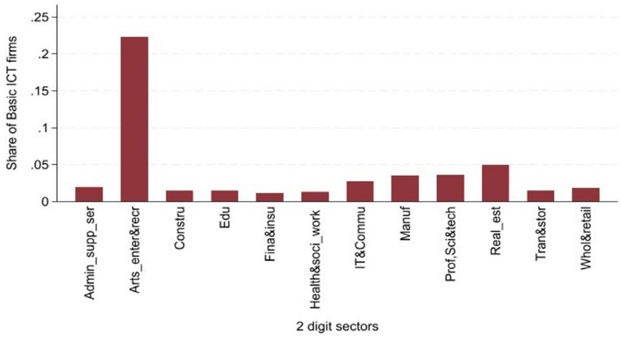

Figure 6: Share of Basic ICT adopters across NIC 2-digit sectors.

4. Which firms adopt digital technologies?

Existing studies have shown that not all firms have the capabilities to engage in all activities, with complex activities typically following simpler ones (Coad et al., 2021). Many firms lack the organizational capabilities required for exporting or conducting R&D, which explains why fewer firms in emerging economies participate in innovative activities (Cirera and Maloney, 2017). In this section, we examine which firms adopt digital technologies, or in other words, we identify the firm characteristics associated with digital technology adoption and explore how these patterns vary across different types of technologies. We estimate the following equation:

$$P(D_{\mathrm{D/NDTA}_{it}} = 1) = \phi(\beta_1 \mathrm{logsales}_{it-1} + \beta_2 \mathrm{R\&Dintensity}_{it-1} + \beta_3 \mathrm{ExportIntensity}_{it-1} + \beta_4 \mathrm{FirmGrowth}_{it-1} + \beta_5 \mathrm{Stafftraining}_{it-1} + \vartheta_i + \tau_t + \gamma_i + \epsilon_{it}) \quad (1)$$

Where $P(D_{D/NDitTA})$ represents the discrete choice of the firm to adopt digital technologies, such as AI, advanced ICT, and basic ICT, as well as non-digital technology adoption. ϕ denotes the Cumulative Distribution Function (CDF) of the standard normal distribution. The independent variables include log sales, R&D intensity, Export intensity, firm growth and staff training, as defined in Table 1. Additionally, τt and γi represent time and sector dummy variables, respectively.

The results are presented in Table 2. Column 1 reports the coefficients with AI Adoption on the left-hand side, Column 2 with Advanced ICT as the dependent variable, Column 3 with Basic ICT as the dependent variable.

AI, Advanced ICT, and Basic ICT adoption are positively associated with larger, high-growth firms. Exporting is positively related to Advanced ICT adoption, but AI and Basic ICT adopters are likely to export less. While AI Adopters seem to spend more on staff training, this is not the case for Advanced and Basic ICT adopters. R&D intensity is not significantly related to any forms of technology adoption. It is important to note that these findings reflect correlations rather than causal relationships, highlighting firm characteristics at the time of adopting different types of digital technologies.

	(1) AI	(2) Advanced ICT	(3) Basic ICT
Log sales	0.075*** (0.006)	0.144*** (0.007)	0.086*** (0.007)

R&D intensity	-0.116 (0.282)	0.077 (0.189)	0.005 (0.223)
Export intensity	-0.577*** (0.081)	0.102* (0.062)	-0.403*** (0.086)
Staff Intensity	0.024*** (0.009)	0.001 (0.019)	-0.006 (0.022)
Firm growth	0.542*** (0.033)	0.685*** (0.037)	0.589*** (0.037)
Year dummies	Yes	Yes	Yes
Sector dummies	Yes	Yes	Yes
Observations	19667	19667	19667
Pseudo R2	0.039	0.085	0.054

Table 2: Determinants of Digital Technology Adoption

*Notes: Standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01*

5. Impact of digital technology adoption on future hirings

In this section, we investigate the impact of digital technology adoption on firms' future hirings and how this effect varies for different types of digital technologies and occupations. Specifically, we examine what happens to future hirings for less advanced digital roles when a firm adopts advanced digital technology. This is detailed in the following.

i) AI Adoption

Let's first consider the case of AI adoption. We investigate whether AI adoption by a firm leads to an increase (or decrease) in hiring for other digital roles, namely Advanced and Basic ICT, as well as non-digital roles. We estimate the following equations:

$$\begin{aligned}\ln(\text{Adv ICT hiring})_{it} = {}& \beta_0 + \beta_1 \text{AIadop}_{it-1} + \beta_2 \text{logsales}_{it-1} + \beta_3 \text{R\&Dintensity}_{it-1} + \\ & \beta_4 \text{ExportIntensity}_{it-1} + \beta_5 \text{FirmGrowth}_{it-1} + \vartheta_i + \tau_t + \gamma_i + \epsilon_{it}\end{aligned} \tag{2}$$

$$\begin{aligned}\ln(\text{Basic ICT hiring})_{it} = {}& \beta_0 + \beta_1 \text{AIadop}_{it-1} + \beta_2 \text{logsales}_{it-1} + \beta_3 \text{R\&Dintensity}_{it-1} + \\ & \beta_4 \text{ExportIntensity}_{it-1} + \beta_5 \text{FirmGrowth}_{it-1} + \vartheta_i + \tau_t + \gamma_i + \epsilon_{it}\end{aligned} \tag{3}$$

$$\begin{aligned}\ln(\text{Non digital hiring})_{it} = {}& \beta_0 + \beta_1 \text{AIadop}_{it-1} + \beta_2 \text{logsales}_{it-1} + \beta_3 \text{R\&Dintensity}_{it-1} + \\ & \beta_4 \text{ExportIntensity}_{it-1} + \beta_5 \text{FirmGrowth}_{it-1} + \vartheta_i + \tau_t + \gamma_i + \epsilon_{it}\end{aligned} \tag{4}$$

In equation 2, the dependent variable is Advanced ICT hiring, while in equation 3, it is Basic ICT hiring, and in equation 4, it is non-digital hiring. Across all equations (2 - 4), the main variable of interest is AI Adoption, represented by a dummy variable that takes the value of 1 if the firm has adopted AI and 0 otherwise. As detailed in the data section, AI adoption is proxied by whether firms have advertised job postings requiring AI skills. The control variables include firm size, measured by the log of sales revenue, as firm size is expected to influence hiring levels. Other control variables capture the complexity of the firm's activities, such as R&D and exporting intensity.[5] We also account for the firm's previous growth momentum (firm growth), proxied by the log difference in sales between time t and $t + 1$. All right-hand-side variables are lagged by one year. Additionally, we control for time effects (τt), sector (θi), and city dummies (γi).

5 The definitions and descriptions of all variables are in Table 1

We begin with an OLS and fixed effects regression. The results are reported in Table 10 and 11 in appendix. The first four columns present the results of equation 2, with Advanced ICT hiring as the dependent variable. Within each of these columns, the coefficients are reported separately for each occupational category: managers, professionals, associate professionals, and others. Columns 5–8 display the results from the estimation of equation 3, where the dependent variable is Basic ICT hiring across different occupational categories. The final set, columns 9–12, reports results with non-digital hiring as the dependent variable, as specified in equation 4. The coefficient of our main variable of interest, AI Adoption, is negative and significant in the first two sets of regressions (from equations 2 and 3), where Advanced ICT hiring and Basic ICT hiring are the dependent variables. This suggests that firms adopting AI tend to reduce future hirings of staff with less advanced digital skills, specifically in Advanced and Basic ICT. We also find that AI adoption leads to increased hiring of non-digital jobs, as seen in table 10 and 11.

However, both OLS and Fixed Effects results suffer from issues of endogeneity (Wooldridge, 2009). First, there could be reverse causality: firms that hire more (or fewer) employees for other digital technologies might subsequently hire for AI-related jobs (our proxy for AI adoption). But the issue of endogeneity extends beyond reverse causality. The fundamental issue is that the firms that adopt AI are not a random sample, but a selected sample. Some of the firm characteristics that determine AI adoption are likely unobservable and might also be correlated with the outcome variable.

To address the first issue of reverse causality, we apply an IV approach (Bingley and Martinello, 2017; Wooldridge, 2003). While this approach is not a panacea—2SLS bias can some- times exceed OLS bias, especially in smaller samples—this concern is mitigated here, as we do not face small sample size issues. Additionally, we conduct various tests to assess the correlation between the instrument and the endogenous regressor, as well as tests for the over-identification of all instruments.

The instrument we use must not be directly correlated with the dependent variable (in this case, different types of digital and non-digital hiring), but should be correlated with a firm's AI (or other advanced digital technology) adoption. We construct our instrumental variable using information on the technology adoption status of other firms within the same sector, as the adoption behavior of competitors is likely to influence a firm's own digital adoption. Therefore, our first IV is the number of firms that adopt AI in the same three-digit sector (to ensure some common technical routines) but in a different four-digit sector (to ensure that there is no direct competition). We want to avoid direct competitors, since an increase in hirings of a competitor might lower the available skills in the market and might reduce (affect) the hiring of the firm in consideration. In the following, we call this variable NFAI. As a second instrument, we use the share of sales of firms who adopt AI technologies in the same three-digit sector, but in a different four-digit sector. We refer to this as SFAI. These instruments are similar to the ones proposed by (Coad et al., 2020). We have tested and proved their non-weakness and validity by checking the F-statistic from the first stage regression, the Kleibergen–Paap tests on weak instruments and underidentification, the Hansen J-Test on overidentifying restrictions for overall instrument validity.

The results from the IV regression are presented in Table 3 where each set of four columns reports results from different independent variables. Columns 1-4 report results with Advanced ICT hiring as the dependent variable, while Columns 5-8 report results with Basic ICT hiring as the dependent variable and the last set, columns 9-12 report results with non-digital hiring as the dependent variable.

As is evident from the results reported in the first eight columns, AI adoption leads to less future hiring of jobs that require Advanced and Basic ICT skills, suggesting a strong negative impact of AI adoption on less advanced digital jobs. These results are very consistent across different occupational categories, including managers, professionals, associate and technical professionals, and other workers.

Conversely, columns 9-12 demonstrate a significantly positive effect of AI adoption on non-digital hiring across these occupational groups. Furthermore, larger enterprises (as indicated by log sales) tend to engage in Advanced ICT and Basic ICT hiring, while smaller firms do more non-digital hiring. R&D and export activities do not seem to have a significant effect in explaining digital and non-digital hiring. Lastly, firms that had a higher growth momentum in the previous year hired less than during the current year.

ii) Advanced ICT Adoption

Following the analysis of AI adoption's impact on less advanced digital technology jobs, we now examine the effect of Advanced ICT adoption on firms' Basic ICT hiring and other non-digital hirings.

	Panel A: Advanced ICT Hiring				Panel B: Basic ICT Hiring			
	(1) Managers	(2) Prof	(3) Asso. Prof	(4) Others	(5) Managers	(6) Prof	(7) Asso. Prof	(8) Others
AI Adoption	-0.213** (0.092)	-0.562*** (0.185)	-0.532*** (0.182)	-0.539*** (0.184)	-1.297*** (0.274)	-1.005*** (0.244)	-0.890*** (0.209)	-0.671*** (0.203)
Log sales	0.014** (0.006)	0.041*** (0.013)	0.034*** (0.012)	0.024** (0.011)	0.013 (0.012)	0.035*** (0.010)	0.020** (0.009)	0.021** (0.010)
R&D intensity	0.002 (0.018)	0.057 (0.069)	0.011 (0.038)	0.025 (0.030)	0.058 (0.048)	0.068 (0.043)	0.033 (0.044)	0.043 (0.042)
Export intensity	-0.056* (0.031)	-0.079 (0.060)	-0.089 (0.063)	-0.069 (0.056)	0.070 (0.087)	0.005 (0.070)	0.053 (0.072)	-0.000 (0.051)
Firm growth	-0.041*** (0.010)	-0.113*** (0.021)	-0.094*** (0.018)	-0.069*** (0.018)	-0.050** (0.024)	-0.061*** (0.022)	-0.042** (0.019)	-0.043** (0.020)
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14710	14710	14710	14710	11484	11058	11939	12412
Centered R2	0.037	0.055	0.055	0.054	0.101	0.119	0.100	0.071
Hansen p-value	0.284	0.048	0.018	0.095	0.335	0.302	0.322	0.270

	Panel C: Non-Digital Hiring			
	(9) Managers	(10) Prof	(11) Asso. Prof	(12) Others
AI Adoption	1.787** (0.754)	2.047** (0.858)	2.298** (0.925)	2.594* (1.524)
Log sales	-0.370* (0.189)	-0.422** (0.167)	-0.357* (0.189)	-0.235 (0.212)
R&D intensity	-6.213 (5.288)	-7.563 (5.056)	-3.230 (4.632)	-4.265 (4.711)
Export intensity	0.757 (0.582)	0.961* (0.577)	0.721 (0.649)	0.966* (0.552)
Firm growth	0.388 (0.250)	0.109 (0.213)	0.215 (0.249)	0.020 (0.258)

Time Dummies	Yes	Yes	Yes	Yes
Sector Dummies	Yes	Yes	Yes	Yes
Observations	977	1075	922	779
Centered R2	0.026	-0.019	0.097	-0.134
Hansen p-value	0.371	0.422	0.267	0.667

Table 3: Effect of AI Adoption on Digital and Non-Digital Hiring

*Notes: Standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01*

We estimate the following equations:

$$\ln(\text{Basic ICT hiring})_{it} = \beta_0 + \beta_1 \text{AdvICTadop}_{it-1} + \beta_2 \text{logsales}_{it-1} + \beta_3 \text{R\&Dintensity}_{it-1} + \beta_4 \text{ExportIntensity}_{it-1} + \beta_5 \text{FirmGrowth}_{it-1} + \vartheta_i + \tau_t + \gamma_i + \epsilon_{it} \tag{5}$$

$$\ln(\text{Non digital hiring})_{it} = \beta_0 + \beta_1 \text{AdvICTadop}_{it-1} + \beta_2 \text{logsales}_{it-1} + \beta_3 \text{R\&Dintensity}_{it-1} + \beta_4 \text{ExportIntensity}_{it-1} + \beta_5 \text{FirmGrowth}_{it-1} + \vartheta_i + \tau_t + \gamma_i + \epsilon_{it} \tag{6}$$

In equations 5 and 6, the main independent variable of interest is Advanced ICT Adoption, which is a dummy variable that takes value 1 if the firm has adopted Advanced ICT technologies and 0 otherwise. The control variables are the same as those in equation 5. Here we investigate the effect of Advanced ICT adoption on Basic ICT hiring (equation 5) and non- digital hiring (equation 6).

We begin with an OLS and Fixed Effects Estimation, the results of which are reported in tables 12 and 13 in the appendix. As in the previous section, we use an IV estimation to address endogeneity. The instrument variables follow the same concept as before: the first IV is the share of firms adopting advanced ICT technology in the same three-digit sector but in a different four-digit sector (SNADV). The second IV is the share of sales from firms that adopt advanced ICT technologies in the same three-digit sector but in a different four-digit sector (SFADV).

	(1) Managers	(2) Prof	(3) Assos.prof	(4) Others	(5) Managers	(6) Prof	(7) Assos.prof	(8) Others
Adv ICT Adoption	-1.617*** (0.387)	-1.021*** (0.320)	-0.669*** (0.259)	-0.686** (0.316)	0.238 (0.394)	1.079*** (0.360)	1.186*** (0.358)	0.991*** (0.379)
Log sales	0.007 (0.012)	0.032*** (0.011)	0.020* (0.010)	0.019* (0.011)	-0.335*** (0.072)	-0.337*** (0.074)	-0.228*** (0.075)	-0.192** (0.079)
R&D intensity	0.015 (0.046)	0.056 (0.044)	0.031 (0.044)	0.044 (0.042)	-2.593 (2.976)	-2.914 (3.077)	-1.621 (3.220)	-2.549 (3.134)
Export intensity	0.059 (0.082)	0.007 (0.070)	0.051 (0.071)	-0.009 (0.050)	0.079 (0.316)	0.078 (0.154)	0.055 (0.326)	0.066 (0.365)
Firm growth	-0.035 (0.025)	-0.057*** (0.022)	-0.043** (0.020)	-0.041* (0.021)	1.331*** (0.122)	1.179*** (0.126)	1.079*** (0.130)	1.074*** (0.140)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Sector dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11484	11058	11939	12412	1824	1934	1693	1471
Centered R2	0.096	0.085	0.066	0.057	0.214	0.216	0.194	0.219
Hensenp	0.662	0.547	0.909	0.883	0.093	0.142	0.367	0.270

Table 4: Effect of Advanced ICT Adoption on Basic ICT and non-digital hiring

*Notes: Standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01*

Table 4 presents the IV regression results of advanced ICT adoption on digital and non digital hirings. Columns 1-4 report outcomes with Basic ICT hiring as the dependent variable, while Columns 5-8 focus on non-digital hiring. The results are consistent with Table 3, indicating that advanced ICT adoption negatively impacts future Basic ICT hiring and positively affects future non-digital hiring. The analysis further indicates that larger firms tend to hire more digital workers while reducing the hiring of non-digital workers. Export and research activities do not appear to have a significant effect on Basic ICT and non-digital hirings. Firms that grew more in the past year hired more non-digital workers and less of workers with Basic ICT skills.

5.1 Propensity score matching

As mentioned earlier, the concerns regarding endogeneity extend beyond reverse causality. A fundamental issue is selection bias, as firms that adopt digital technologies differ from those that do not, a finding we also observe empirically, with results reported in Table 2.

To deal with the selection bias, we employ a Propensity Score Matching (PSM) technique, which takes into account the selection into the treatment (Adoption of AI, ICT etc.) based on observables (Rosenbaum and Rubin, 1983). We employ a logit model to estimate the determinants of digital technology adoption (namely, AI, Advanced and Basic ICT) and then the propensity score matching is implemented with a nearest-neighbor method (one-to-one matching) and replacement.

Following matching, the Average Treatment Effect on the Treated (ATET) and the Average Treatment Effect on the Untreated (ATU) are estimated. The ATET measures the treatment effect on units that received the treatment:

$$\text{ATET} = \mathrm{E}[Y(1) - Y(0) \mid T = 1]$$

Where Y (1) and Y (0) represent potential outcomes with and without the treatment, respectively. The ATU measures the - counterfactual - potential effect on units that did not receive the treatment if they had received:

$$\text{ATU} = \mathrm{E}[Y(1) - Y(0) \mid T = 0]$$

Table 5 reports the ATET and ATU after estimating the effect of AI Adoption on digital and non-digital hiring (results of estimating the equations 2 - 4). As before, each 4 sets of columns report results for Advanced ICT hiring, Basic ICT hiring and non-digital hiring.

As reported in Table 5, columns (1) to (8), the Average Treatment Effect on the Treated (ATET) is negative and significant for nearly all occupational categories, except for managers. This suggests that firms which adopted AI reduced hiring for three occupational categories that required both advanced and basic ICT skills. For managers, there is no significant effect, indicating that hiring managers with AI skills does not significantly lower the probability of future hirings of managers with less advanced digital skills. However, the findings for non-digital jobs align with our earlier observations: across all occupational categories, firms that adopted AI have increased their hiring of non-digital positions.

When looking at the coefficient of ATET, the only consistent and significant results are for the category of non-digital jobs, where the ATET is negative and significant. This suggests that firms which did not adopt AI would not have experienced increased hiring for non-digital jobs, even if they had adopted AI. This indicates that firms that actually adopted AI were at a growth or capability stage that enabled them to adopt the technology and benefit from it, leading to growth and increased hiring. In contrast, firms that did not adopt AI likely lacked the capabilities to do so and would have had to reduce hiring or even shrink to accommodate the investment in AI.

Similarly, the results on the effect of Advanced ICT adoption on Basic ICT and non-digital hiring show a comparable pattern. As indicated in Table 6, the negative and significant ATET indicates that Advanced ICT adoption leads to a reduction in hiring of professionals and as- sociate professionals with Basic ICT skills, while there is no significant effect on the hiring of managers. The results for non-digital hiring indicate that Advanced ICT adoption leads to an increase in hiring across all occupational categories, requiring non-digital skills. In short, we observe a substitution effect between more advanced and less advanced digital skills where AI is substituting Advanced and Basic ICT, and Advanced ICT in turn substituting Basic ICT.

6. Digital Technologies: Hiring and Training

The external and internal environment in which a firm operates (among others, institutions, availability of internal and external skills,) could significantly impact firm-level technology adoption. As discussed earlier in section 5, during the technology adoption process, firms often face a choice between training existing employees, hiring new employees, or employing a combination of both. According to previous studies, one barrier to technology adoption is the lack of skills (Dalmarco et al., 2019; Fantini et al., 2020; Karadayi-Usta, 2019; Stentoft and Rajkumar, 2020), which may prompt firms to rely on external hiring. This external hiring becomes even more likely when the “new knowledge” required for adoption is far from the firm’s “existing knowledge” base, which new employees are expected to bring in. At the same time, the resource-based theory of the firm argues that a firm’s competitive advantage lies in its ‘non-transferable’ and ‘non-imitable’ skills, which are embedded in the employees and teams within the organization. Due to the importance of these tacit skills, firms may prefer to invest in training existing employees rather than hiring new ones.

	Panel A: Advanced ICT Hiring				Panel B: Basic ICT Hiring			
	(1) Managers	(2) Prof	(3) Asso. Prof	(4) Others	(5) Managers	(6) Prof	(7) Asso. Prof	(8) Others
ATET	-0.047 (-1.69)	-0.221*** (-3.49)	-0.218*** (-3.61)	-0.169** (-2.82)	-0.010 (-1.69)	-0.415** (-3.49)	-0.218*** (-3.61)	0.148* (-2.82)
ATU	0.086 (0.55)	0.250 (0.84)	0.069 (0.93)	0.048 (0.65)	0.148 (0.40)	1.258*** (9.69)	0.200 (1.85)	-0.118** (-3.04)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8981	8981	8981	8981	4386	4386	4386	4386

	Panel C: Non-Digital Hiring			
	(9) Managers	(10) Prof	(11) Asso. Prof	(12) Others
ATET	0.886*** (10.97)	0.879*** (11.97)	0.867*** (10.65)	0.967** (10.22)
ATU	-0.532*** (-4.48)	-0.507* (-2.24)	-0.849*** (-3.45)	-0.700*** (-4.85)
Controls	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes
Sector Dummies	Yes	Yes	Yes	Yes
Observations	8981	8981	8981	8981

Table 5: Effect of AI Adoption on Digital and Non-Digital Hiring (PSM)

*Notes: Standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01*

	(1) Managers	(2) Prof	(3) Asso.prof	(4) Others	(5) Managers	(6) Prof	(7) Asso. prof	(8) Others
ATET	-0.231 (-1.77)	-0.203*** (-1.37)	-0.263** (-2.91)	0.105 (1.64)	0.457*** (0.097)	0.475*** (0.096)	0.525*** (0.090)	0.539*** (0.097)
ATU	0.583 (1.53)	0.104 (0.97)	0.0170 (0.18)	0.0034 (0.04)	-0.505 (0.156)	-0.566*** (0.157)	-0.676*** (0.192)	-0.540*** (0.166)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4386	4006	5016	5700	2884	2939	2647	2389

Table 6: Effect of Advanced ICT Adoption on Basic ICT and Non-Digital Hiring (PSM)

*Notes: Standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01*

Empirically documenting the complementarity or substitutability between training and hiring has been challenging due to the lack of data on labor flows within firms and the difficulty in understanding the causal links between the two. Some studies suggest that technological and organizational innovation drives greater investment in training (Antonelli et al., 2010; Lynch and Black, 1998), and also the opposite effect, that training itself leads to increased innovation (Acemoglu and Pischke, 1999; Lorenz and Lundvall, 2006).

In this work, given the data constraints, we explore the relationship between new digital hiring and training of existing employees, examining whether a significant relationship exists between the two. However, we do not make any causal claims regarding this relationship.

We estimate the following equation:

$$Ln(\text{Digital hirings})_{it} = \beta_0 + \beta_1 \,\textbf{Stafftraining}_{\textbf{it-1}} + \beta_2 \,\text{logsales}_{it-1} + \beta_3 \,\text{R\&Dintensity}_{it-1} + \beta_4 \,\text{ExportIntensity}_{it-1} + \beta_5 \,\text{FirmGrowth}_{it-1} + \vartheta_i + \tau_t + \gamma_i + \epsilon_{it} \quad (7)$$

Where *Ln*(Digital hirings)$_{it}$ is the log of total unique job posts made by firm *i* at time *t* that requires a kind of digital skill. We run fixed effects regressions. The dependent variable, *Ln*(Digital hirings)$_{it}$ takes different forms. In the first set of regressions, these skills refer to AI skills. The regressions are performed across four different occupation categories, with the results shown in Columns 1-4 of Table 7. After AI hiring, the next set of regressions focuses on advanced ICT hiring, followed by basic ICT hiring. Separate regressions are run for each digital skill type, and within each, the analysis is conducted across different occupation categories.

In Table 7, Columns 5–8 display the results using Advanced ICT hiring as the dependent variable, while Columns 9–12 present the results for Basic ICT hiring.

We performed a fixed effects regression to examine the relationship between staff training and hirings of jobs that need different kinds of digital skills. A positive relationship between investments in staff training and the hiring of jobs requiring advanced skills, such as AI and advanced ICT, is observed only in one occupation category—managers. No significant results were found for the other categories.

	Panel A: AI Hirings				**Panel B: Advanced ICT Hirings**			
	(1) Managers	**(2) Prof**	**(3) Asso. Prof**	**(4) Others**	**(5) Managers**	**(6) Prof**	**(7) Asso. Prof**	**(8) Others**
Staff training	0.274*** (0.088)	0.006 (0.176)	-0.718* (0.390)	-0.086 (0.165)	0.267** (0.117)	0.087 (0.102)	-0.343 (0.291)	-0.080 (0.132)
Log sales	0.086 (0.102)	-0.249 (0.218)	0.295* (0.153)	-0.153 (0.096)	0.083 (0.136)	0.043 (0.127)	-0.078 (0.114)	-0.053 (0.077)
R&D intensity	2.460 (5.209)	0.828 (12.627)	-24.641** (12.315)	0.442 (4.007)	8.055 (6.927)	-15.401** (7.344)	-13.903 (9.194)	-3.373 (3.214)
Export intensity	-0.149 (0.256)	0.447 (0.577)	-0.344 (0.481)	0.307 (0.401)	0.096 (0.341)	-0.026 (0.335)	-1.417*** (0.359)	0.185 (0.322)
Firm growth	-0.003 (0.062)	-0.245 (0.199)	-0.146 (0.138)	-0.292*** (0.077)	-0.035 (0.083)	-0.002 (0.116)	0.117 (0.103)	-0.034 (0.062)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	632	1119	1282	2654	632	1119	1282	2654
Adjusted R2	0.763	-0.122	0.478	0.498	0.627	0.421	0.277	0.200

	Panel C: Basic ICT Hirings			
	(9) Managers	**(10) Prof**	**(11) Asso. Prof**	**(12) Others**
Staff training	-0.005 (0.043)	-0.017 (0.095)	-0.041 (0.190)	-0.113 (0.126)

Log sales	-0.050 (0.050)	-0.102 (0.118)	-0.071 (0.074)	-0.151** (0.073)
R&D intensity	0.748 (2.540)	-2.193 (6.816)	-2.561 (5.994)	0.223 (3.068)
Export intensity	0.308** (0.125)	-0.082 (0.311)	-0.455* (0.234)	0.286 (0.307)
Firm growth	0.003 (0.030)	0.043 (0.107)	-0.057 (0.067)	-0.085 (0.059)
Year Dummies	Yes	Yes	Yes	Yes
Observations	632	1119	1282	2654

Table 7: Staff Training and Digital and Non-Digital Hirings

*Notes: Standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01*

7. Digital hiring, Training and Firm Performance

As discussed in the previous section, firms may adopt different strategies for adopting new digital technologies: hiring, training, or a combination of both. In this section, we assess which of these strategies yield better performance for the firm, measured in terms of sales growth.

We estimate the following equations:

$$FG_{it} = \alpha + \beta X_{it} + \gamma AI_{it} + \rho ST_{it} + \phi(AI_{it} \times ST_{it}) + \tau_t + \epsilon_{it} \tag{8}$$

$$FG_{it} = \alpha + \beta X_{it} + \gamma AdvICT_{it} + \rho ST_{it} + \phi(AdvICT_{it} \times ST_{it}) + \tau_t + \epsilon_{it} \tag{9}$$

$$FG_{it} = \alpha + \beta X_{it} + \gamma BasicICT_{it} + \rho ST_{it} + \phi(BasicICT_{it} \times ST_{it}) + \tau_t + \epsilon_{it} \tag{10}$$

We begin with a fixed effects estimation, results of which are presented in Table 8. In column 1, we present the results of equation 8, with AI_{it}, ST_{it} and $AI_{it} \times ST_{it}$ as our main independent variables and FG_{it} representing firm growth calculated as the log difference in sales between *t* & *t-1* as dependent variable. ST_{it} is a dummy variable that takes value 1 if firms spend on staff training and zero otherwise. Column 2 reports results of equation 9 with $AdvICT_{it}$, ST_{it} and $AdvICT_{it} \times ST_{it}$ and Column 3 reports results of equation 10 with $BasicICT_{it}$, ST_{it} and $\mathrm{BasicICT}_{it} \times \mathrm{ST}_{it}$ as our main independent variables. We include control variables, represented by X_{it} in the equation, that are expected to affect firm growth, such as firm size, R&D intensity, and export intensity. We also control for time fixed effects.

The results from Column 1 show that both AI adoption and staff training significantly influence firm growth. Additionally, the interaction term is significant, indicating that combining AI adoption with staff training enhances firm growth. In Column 2, we observe that staff training has a positive significant influence on firm growth, while Advanced ICT itself and its interaction with staff training do not show significant results. Additionally, in column 3, basic ICT adoption is not associated with firm growth, nor does the interaction between basic ICT and staff training significantly explain firm growth. As mentioned earlier, the coefficients we observe may be biased due to self-selection. Firms that adopt technologies are inherently different from those that do not, a finding we also empirically observe in Section 4, as reported in the results in Table 2. Further, it is also likely that firms investing in staff training differ from those that do not. Therefore, we face a dual selection issue, with respect to two aspects we are studying: Firm-level Technology Adoption and Staff Training.

We apply here a Propensity Score Matching to tackle the dual selection issue (Li, 2013). Therefore, we will have two latent variables: i) The first latent variable determines which firms adopt different technologies (equation 11) and ii) the second latent variable determines which firms invest in staff training (equation 12). And we will have 4 equations (equations 13 - 16) representing the different regimes for the technology adopters and investors for staff training, specifically: i) Regime 1, where firms adopt technology and invest in staff training, ii) Regime 2, where firms adopt technology but do not invest in staff training, iii) Regime 3, where firms do not adopt technology but invest in staff training, iv) Regime 4, where firms neither adopt technology nor invest in staff training.

In all the analysis (and equations 11 - 16), the term TA_{it} takes three forms, namely AI Adoption, Advanced ICT adoption, and Basic ICT adoption.

	(1) AI*ST	(2) ADVICT*ST	(3) ICT*ST
Log sales	-0.201*** (0.009)	-0.158*** (0.008)	-0.219*** (0.023)
R&D intensity	-0.701*** (0.173)	-0.710*** (0.207)	-5.340*** (0.997)
Export intensity	0.034 (0.026)	-0.149*** (0.032)	0.066 (0.081)
Staff training	0.040*** (0.015)	0.068*** (0.015)	0.026 (0.035)
AI Adoption	0.061*** (0.022)		
Training*AI interaction	0.047** (0.018)		
Adv ICT Adoption		-0.028 (0.019)	
Training*ADVICT Interaction		0.015 (0.020)	
ICT Adoption			-0.020 (0.040)
Training*ICT interaction			-0.050 (0.038)
Year Dummies	Yes	Yes	Yes
Observations	19667	23889	6955
Adjusted R2	0.152	0.049	0.182

Table 8: FE: Firm growth and technology adoption, training

*Notes: Standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01*

$$TA_{it} = \begin{cases} 1 & \text{if} \quad \gamma Z_{it} + \mu_{it} > 0, \\ 0 & \text{if} \quad \gamma Z_{it} + \mu_{it} \leq 0. \end{cases} \tag{11}$$

$$ST_{it} = \begin{cases} 1 & \text{if} \quad \theta Z_{it} + \mu_{it} > 0, \\ 0 & \text{if} \quad \theta Z_{it} + \mu_{it} \leq 0. \end{cases} \tag{12}$$

$$Regime \quad 1: \quad y_{1it} = \beta_1 X_{1it} + \epsilon_{1it}, \quad if \quad TA_{it} = 1 \quad \& \quad ST_{it} = 1 \tag{13}$$

$$Regime \quad 2: \quad y_{2it} = \beta_2 X_{2it} + \epsilon_{2it}, \quad if \quad TA_{it} = 1 \quad \& \quad ST_{it} = 0 \tag{14}$$

$$Regime \quad 3: \quad y_{3it} = \beta_3 X_{3it} + \epsilon_{3it}, \quad if \quad TA_{it} = 0 \quad \& \quad ST_{it} = 1 \tag{15}$$

$$Regime \quad 4: \quad y_{4it} = \beta_4 X_{4it} + \epsilon_{4it}, \quad if \quad TA_{it} = 0 \quad \& \quad ST_{it} = 0 \tag{16}$$

The dependent variables y_{ji} (j = 1, 2, 3, 4) correspond to firm growth in all four regimes. $\beta 1$, $\beta 2$, $\beta 3$, $\beta 4$, γ and θ are vectors of parameters that are jointly estimated (instead of being estimated via a two-step procedure) using a Full Information Maximum Likelihood (FIML) method. This provides us with an efficient method to compute the counterfactuals for the four different scenarios:

- The effect of investing in staff training and adopting technology for firms that actually invested in staff training and adopted technology (i.e. the Average Treatment effect on the Treated, the ATT_1), and the counterfactual effect for firms that adopted technology but did not invest in staff training, (i.e. the Average Treatment effect on the Untreated, the ATU_1).
- The effect of investing in staff training and adopting technology for firms that actually in- vested in staff training and adopted technology ATT_2 (similar to ATT_1), and the counterfactual effect for firms that did spend on staff training and did not adopt technology (ATU_2).
- The effect of *only* adopting technology for firms that actually adopted technology (and did not spend on staff training) (ATT_3) versus the counterfactual effect for firms that neither adopted technology nor invested in staff training (ATU_3).
- The effect of only staff training investment for firms that actually invested in staff training (and did not adopt technology) (ATT4) against the counterfactual effect for firms that neither adopted technology nor invested in staff training (ATU_4).

The results are reported in Table 9. The three different columns correspond to the different kinds of technology adoption, namely, AI, Advanced ICT, and Basic ICT. The four horizontal blocks represent the different scenarios. ATT1 is positive and significant in column 1 indicating that the firms that actually adopted AI and spent on staff training had higher firm growth. This finding holds for Advanced and Basic ICT adoption, as shown in Columns 2 and 3. The positive and significant ATU1 values suggest that firms that adopted digital technology but did not invest in staff training would have seen better growth if they had also invested in staff training. In other words, firms are missing out on growth potential by adopting technologies without simultaneously investing in staff training. In the second set of results, ATT2 is also positive and significant, indicating that firms that adopted digital technologies and invested in staff training experienced higher firm growth. The positive and significant ATU2 value for advanced ICT suggests that firms which did not adopt advanced ICT but invested in staff training would have achieved better growth had they also invested in advanced ICT technology adoption.

When considering the effect of technology adoption alone, the positive and significant ATT3 values are only for AI adoption, indicating that firms adopting AI technologies experience higher growth even without investments in staff training. In contrast, ATU3 is not significant, indicating that firms that did not adopt digital technologies would not have benefited from doing so anyway. This is likely because these firms lack the necessary capabilities to fully leverage the potential of digital technologies, which may explain why they have not adopted them. Similarly, Coad et al. (2020) reports analogous findings in the context of R&D and firm performance, showing that firms that do not invest in R&D would not achieve significant sales growth even if they had made such investments.

Finally, we do not find any effect of investment in staff training alone on firm growth, as indicated by the ATT_4 values. This aligns with findings from other studies, which suggest that while staff training may not yield short-term benefits for firms, it can be advantageous for both workers and firms in the long run.

In summary, our findings highlight that staff training plays a crucial role during periods of technology adoption, as it enables firms to maximize the potential benefits of digital technologies and improve their future performance. Better put, ad hoc hiring is not an effective strategy for digital technology adoption, as it fails to address the need for building the internal capabilities required to fully leverage these technologies.

	(1) AI	(2) ADV ICT	(3) ICT
ATT1 (TA=1, ST=1)	0.115*** (0.035)	0.138*** (0.050)	0.112*** (0.054)
ATU1(TA=1, ST=0)	0.889*** (0.034)	0.746*** (0.043)	0.748 *** (0.051)
Observations			
Adjusted R2			
ATT2 (TA=1, ST=1)	0.128*** (0.025)	0.131*** (0.010)	0.161*** (0.083)
ATU2(TA=0, ST=1)	0.020 (0.027)	0.098*** (0.012)	0.007 (0.100)
Observations			
Adjusted R2			
ATT3(TA=1, ST=0)	0.99** (0.574)	0.605 (0.405)	0.076 (0.485)
ATU3(TA=0, ST=0)	0.701 (0.574)	0.693 (0.405)	0.655 (0.480)
Observations			
Adjusted R2			
ATT4(TA=0, ST=1)	0.283 (0.283)	0.283 (0.283)	0.283 (0.283)
ATU4(TA=0, ST=0)	0.695 (0.283)	0.695 (0.283)	0.695 (0.283)

Year Dummies	Yes	Yes	Yes
Sector Dummies	Yes	Yes	Yes

Table 9: PSM: Firm growth, Technology adoption and training

*Notes: Standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01*

8. Conclusion

In this study, we use a novel matched dataset of firm-level and online job vacancy data to investigate the dynamics of hiring and training associated with digital technology adoption at the firm level, differentiating across various types of technologies and occupational categories.

First, we examine the impact of adopting different types of digital technologies—namely AI, Advanced ICT, and Basic ICT—on firms' future hirings patterns. Our findings reveal that the adoption of advanced digital technology leads to fewer hirings of less advanced digital jobs, that is, less advanced digital skills are being substituted by more advanced digital skills. However, the adoption of advanced technologies by firms leads to a rise in overall hiring for non-digital roles. Second, we show that hiring in firms is positively associated with on-the-job training, but only for high-skilled occupations, particularly managerial roles, while no significant relationship is observed for other occupations. Third, we explore the combined effect of training and technology adoption on firm performance. Notably, we find that technology adoption enhances firm performance only when paired with internal training, a pattern that holds true for Basic ICT and Advanced ICT adoption. The exception lies in AI adoption, where firms achieve performance gains even without staff training. However, similar to the case of other technologies, also when AI adoption is combined with staff training, firms experience positive performance outcomes.

Our study has significant implications for academics, policy stakeholders, and firm managment. From an academic perspective, the study emphasizes that the broad question of how technology adoption affects employment is a complex issue that, when disaggregated, reveals several layers of nuanced information, including significant heterogeneities across various dimensions. Our findings show that the impact of digital technologies on employment could vary depending on the type of occupation. Analyzing these effects at a more granular level provides valuable insights into who benefits and who loses as firms adopt digital technologies. Future studies could explore similar heterogeneities in technology and employment or consider other detailed classifications of workers or segments of society.

Another important consideration is that when examining the effects of firm activities or investments—such as technology adoption or staff training—on performance, it is essential to acknowledge that firms vary in their capabilities to implement these activities or fully benefit from such investments. Consequently, it is crucial to examine these effects using robust econometric techniques to accurately assess the impact of such firm activities and investments on their future performance.

Further, our results indicate that during the process of technology adoption and related organizational changes, it is critically important for firm management to invest in staff training alongside new hiring. This would ensure a balanced mix of employees, helping to maintain and enhance organizational routines while simultaneously upgrading the firm's knowledge base.

The main policy implication derived from our study is that incentives for technology adoption should be paired with firm-level incentives for staff training. Additionally, understanding that technology impacts occupations differently is essential for designing strategies, including targeted training programs, to promote greater equity in society over time.

Our study has several limitations. For instance, we have access only to employment flow data rather than the total stock of employees at the firm level, meaning we do not observe both hiring and separations, which would have allowed us to measure net job creation or destruction. Additionally, since our analysis relies on online job vacancy data, sectors and occupations that are less likely to advertise positions online may be underrepresented—particularly vocational jobs such as carpenters, electricians, and similar trades. Access to more detailed employer-employee matched data, combined with firm-level information, could provide deeper insights into net job creation or destruction at the firm level.

Appendix

	Panel A: Advanced ICT Hiring				Panel B: Basic ICT Hiring			
	(1) Managers	(2) Prof	(3) Asso. Prof	(4) Others	(5) Managers	(6) Prof	(7) Asso. Prof	(8) Others
AI Adoption	-0.280*** (0.0164)	-0.786*** (0.0363)	-0.761*** (0.0359)	-0.730*** (0.0352)	-1.453*** (0.0659)	-1.784*** (0.0681)	-1.408*** (0.0641)	-1.127*** (0.0576)
Log sales	-0.0141*** (0.00120)	-0.0344*** (0.00261)	-0.0330*** (0.00255)	-0.0305*** (0.00249)	-0.0291*** (0.00293)	-0.0250*** (0.00276)	-0.0232*** (0.00263)	-0.0247*** (0.00262)
R&D intensity	-0.0240 (0.0224)	-0.0392 (0.0425)	-0.0367 (0.0373)	-0.0195 (0.0273)	-0.0193 (0.0338)	-0.0159 (0.0322)	-0.0334 (0.0412)	-0.0170 (0.0279)
Export intensity	-0.0362** (0.0164)	-0.0818** (0.0364)	-0.0870** (0.0370)	-0.0860** (0.0347)	0.0255 (0.0328)	0.0619** (0.0314)	0.0494* (0.0291)	0.0716** (0.0288)
Firm growth	-0.0473*** (0.00543)	-0.131*** (0.0113)	-0.130*** (0.0106)	-0.121*** (0.0103)	-0.175*** (0.0145)	-0.159*** (0.0143)	-0.139*** (0.0125)	-0.128*** (0.0125)
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19667	19667	19667	19667	15211	14830	15816	16457
Adjusted R2	0.068	0.110	0.111	0.110	0.176	0.217	0.183	0.144

	Panel C: Non-Digital Hiring			
	(9) Managers	(10) Prof	(11) Asso. Prof	(12) Others
AI Adoption	1.001*** (0.0538)	0.955*** (0.0538)	0.990*** (0.0568)	1.095*** (0.0596)
Log sales	0.0715*** (0.0147)	0.0821*** (0.0143)	0.0842*** (0.0150)	0.0918*** (0.0159)
R&D intensity	-1.122 (1.116)	-0.672 (1.048)	-0.865 (1.027)	-0.791 (1.391)
Export intensity	-0.189* (0.111)	-0.129 (0.0926)	-0.157 (0.103)	-0.134 (0.0982)
Firm growth	0.579*** (0.0626)	0.657*** (0.0631)	0.681*** (0.0685)	0.623*** (0.0703)
Time Dummies	Yes	Yes	Yes	Yes
Sector Dummies	Yes	Yes	Yes	Yes
Observations	2846	2900	2615	2365

Adjusted R2	0.159	0.151	0.160	0.180

Table 10: OLS: AI Adoption on Digital and Non-Digital Hiring

*Notes: Standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01*

	Panel A: Advanced ICT Hiring				Panel B: Basic ICT Hiring			
	(1) Managers	(2) Prof	(3) Asso. Prof	(4) Others	(5) Managers	(6) Prof	(7) Asso. Prof	(8) Others
AI Adoption	-0.246*** (0.0114)	-0.651*** (0.0236)	-0.640*** (0.0229)	-0.610*** (0.0218)	-1.192*** (0.0365)	-1.340*** (0.0395)	-1.080*** (0.0321)	-0.872*** (0.0289)
Log sales	0.00835* (0.00468)	0.0303*** (0.00972)	0.0286*** (0.00942)	0.0307*** (0.00897)	0.0129 (0.0110)	0.0154 (0.0108)	0.0169* (0.00969)	0.0181* (0.00956)
R&D intensity	0.0206 (0.0794)	0.0401 (0.165)	0.0504 (0.160)	0.0649 (0.152)	0.0492 (0.169)	0.00371 (0.167)	0.0459 (0.158)	0.0251 (0.151)
Export intensity	-0.0430* (0.0220)	-0.121*** (0.0457)	-0.172*** (0.0443)	-0.161*** (0.0422)	0.0313 (0.0617)	0.0178 (0.0609)	-0.0215 (0.0542)	-0.0336 (0.0521)
Firm growth	-0.0589*** (0.00668)	-0.172*** (0.0139)	-0.173*** (0.0134)	-0.159*** (0.0128)	-0.174*** (0.0160)	-0.164*** (0.0160)	-0.143*** (0.0144)	-0.131*** (0.0138)
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19667	19667	19667	19667	15211	14830	15816	16457
Adjusted R2	0.107	0.177	0.173	0.180	0.291	0.317	0.303	0.290

	Panel C: Non-Digital Hiring			
	(9) Managers	(10) Prof	(11) Asso. Prof	(12) Others
AI Adoption	0.801*** (0.0931)	0.818*** (0.0917)	0.779*** (0.1000)	0.921*** (0.106)
Log sales	-0.366*** (0.0679)	-0.420*** (0.0691)	-0.314*** (0.0707)	-0.273*** (0.0754)
R&D intensity	-3.533 (2,921)	-3.387 (3.005)	-1.552 (3.119)	-3.018 (3.070)
Export intensity	0.126 (0.310)	0.0492 (0.151)	0.120 (0.317)	0.133 (0.358)
Firm growth	1.298*** (0.0890)	1.361*** (0.0886)	1.293*** (0.0914)	1.227*** (0.0978)
Time Dummies	Yes	Yes	Yes	Yes

Sector Dummies	Yes	Yes	Yes	Yes
Observations	2846	2900	2615	2365
Adjusted R2	0.393	0.388	0.408	0.421

Table 11: FE: AI Adoption on Digital and Non-Digital Hiring

*Notes: Standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01*

	Managers	Prof	Assos. Prof	Others	Managers	Prof	Assos. Prof	Others
Adv ICT Adoption	-1.684*** (0.0687)	-1.488*** (0.0652)	-1.349*** (0.0633)	-1.125*** (0.0592)	0.417*** (0.0568)	0.488*** (0.0567)	0.437*** (0.0595)	0.496*** (0.0633)
Log sales	-0.0232*** (0.00285)	-0.0225*** (0.00289)	-0.0177*** (0.00262)	-0.0203*** (0.00262)	0.0433*** (0.0157)	0.0485*** (0.0149)	0.0615*** (0.0160)	0.0611*** (0.0169)
R&D intensity	-0.00859 (0.0299)	-0.00850 (0.0325)	-0.0159 (0.0341)	-0.00151 (0.0249)	-1.052 (1.473)	-0.751	-0.734	-0.340
Export intensity	0.0807*** (0.0308)	0.131*** (0.0314)	0.107*** (0.0284)	0.120*** (0.0288)	-0.438** (0.189)	-0.366** (0.159)	-0.397** (0.176)	-0.413** (0.192)
Firm growth	-0.157*** (0.0144)	-0.155*** (0.0146)	-0.135*** (0.0128)	-0.125*** (0.0127)	0.551*** (0.0667)	0.590*** (0.0673)	0.619*** (0.0727)	0.545*** (0.0773)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15211	14830	15816	16457	2846	2900	2615	2365
Adjusted R2	0.189	0.165	0.157	0.127	0.058	0.071	0.068	0.069

Table 12: OLS: Adv ICT Adoption on digital and non digital hiring

*Notes: Standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01*

	(1) Managers	(2) Prof	(3) Assos. Prof	(4) Others	(5) Managers	(6) Prof	(7) Assos. Prof	(8) Others
Adv ICT Adoption	-1.363*** (0.0384)	-1.093*** (0.0367)	-1.043*** (0.0325)	-0.843*** (0.0300)	0.555*** (0.0836)	0.607*** (0.0810)	0.595*** (0.0844)	0.661*** (0.0923)
Log sales	0.00708 (0.0110)	0.0107 (0.0110)	0.0128 (0.00974)	0.0157 (0.00961)	-0.318*** (0.0689)	-0.366*** (0.0699)	-0.259*** (0.0711)	-0.207*** (0.0764)
R&D intensity	-0.000989 (0.167)	-0.0240 (0.169)	0.0224 (0.159)	0.0198 (0.151)	-2.559 (2.956)	-2.785 (3.032)	-1.127 (3.133)	-2.431 (3.109)
Export intensity	0.0495 (0.0612)	0.0268 (0.0616)	-0.0163 (0.0544)	-0.0312 (0.0524)	0.0791 (0.314)	0.0688 (0.152)	0.0492 (0.319)	0.0442 (0.362)

Firm growth	-0.150*** (0.0159)	-0.151*** (0.0162)	-0.134*** (0.0145)	-0.123*** (0.0139)	1.264*** (0.0913)	1.294*** (0.0912)	1.229*** (0.0937)	1.160*** (0.101)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15211	14830	15816	16457	2846	2900	2615	2365
Adjusted R2	0.302	0.301	0.297	0.283	0.378	0.376	0.402	0.405

Table 13: FE: Adv ICT Adoption on digital and non digital hiring

*Notes: Standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01*

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