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Technological path-dependency in AI adoption: Evidence from Italian firms

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Technological path-dependency in AI adoption: Evidence from Italian firms

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CONTENTS: 1. Introduction. – 2. Background. – 3. Data and Descriptive Statistics. – 4. Empirical analysis. – 5. Conclusions. – References

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ABSTRACT

Technological path-dependency in AI adoption: Evidence from Italian firms

Prior investments in advanced digital technologies encourage AI adoption. Yet AI integrates differently across technologies depending on existing human-technology relations. When combined with robotics, it tends to reinforce labor substitution; when matched with advanced information technologies (AIT) – such as big data – it supports human-machine complementarity. Firm-level evidence from a large sample of Italian firms supports this distinction. Results show that while prior investments in robotics and AIT are positively associated with AI adoption, only AIT facilitate investments in AI-related training, suggesting that workforce upskilling plays a minor role when AI operates in machine-machine configuration. Additional evidence shows that organizational practices, sectoral conditions, and pre-existing capabilities all play a mediating role. Indeed, AI adoption is more common among firms that invest in worker engagement and operate in industrial sectors, while fiscal incentives support adoption only among already digitalized firms, underscoring the importance of firms' technological readiness.

KEYWORDS: artificial intelligence, digital technologies, technological path-dependency, workforce training
JEL CODES: O33, J24, M15

I precedenti investimenti in tecnologie digitali avanzate favoriscono l'adozione dell'intelligenza artificiale. Tuttavia, l'IA si integra in modo diverso tra le varie tecnologie a seconda delle relazioni già esistenti tra esseri umani e tecnologia. Combinata con la robotica, l'IA tende a rafforzare la sostituzione del lavoro umano; associata invece a tecnologie informatiche avanzate (AIT), come il big data, promuove la complementarità uomo-macchina. L'analisi di un ampio campione di imprese italiane conferma questa distinzione: mentre investimenti precedenti in robotica e AIT sono entrambi correlati positivamente all'adozione dell'IA, solo le AIT incentivano la formazione legata all'IA, indicando un ruolo limitato dell'upskilling quando l'IA opera in configurazioni "macchina-macchina". Infine, pratiche organizzative, caratteristiche settoriali e capacità pregresse mediano il processo di adozione: l'IA risulta più diffusa tra le imprese che coinvolgono i lavoratori e che operano nel settore dell'industria, mentre gli incentivi fiscali sono efficaci solo per le aziende già digitalizzate, evidenziando l'importanza della maturità tecnologica.

PAROLE CHIAVE: intelligenza artificiale, tecnologie digitali, dipendenza dal percorso tecnologico, formazione professionale

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1. Introduction

The economic and social implications of recent advances in Artificial Intelligence (AI) have drawn increasing attention (Agrawal *et al.* 2018a, 2018b, 2019; Brynjolfsson *et al.* 2019, 2025). Often described as the cornerstone of a new industrial revolution, AI is widely regarded as a general-purpose technology that – like steam, electricity, and ICTs before it – is expected to transform the world of work and production (Schwab 2016). Yet, while its impact on human labor is widely debated (Acemoglu and Restrepo 2019a, 2019b, 2020), its heterogeneous use across firms remains poorly understood. Indeed, limited availability of firm-level data still hampers researchers' ability to investigate the organizational, workforce-related, and sectoral conditions that affect its adoption (Calvino and Fontanelli 2023).

Using longitudinal data on Italian firms for the period 2018-2021, this paper is the first - to the best of our knowledge – to examine whether past adoption of different advanced digital technologies facilitates subsequent investments in AI and AI-related training. To guide the empirical analysis, the paper develops a conceptual distinction between Advanced Information Technologies (AIT) – big data, augmented reality, and the Internet of Things – and Robotics. Building on the idea that robots replace human input in repetitive or physical tasks, while advanced information technologies support cognitive work and decision-making, the paper argues that AI integration reflects and reinforces these human – technology relations – of substitution versus augmentation[1]. When coupled with robotics, AI tends to operate in a machine-machine configuration that requires minimal workforce upskilling; when paired with AIT, it operates in a human-machine complementarity framework where worker engagement is more important. This perspective is consistent with the task-based view of technological change (Autor *et al.* 2003), and with recent works analyzing how tasks and occupations mediate the impact of automation technologies (Frey and Osborne 2017).

Our estimates from probit models and propensity score matching confirm this distinction. While lagged adoption of advanced information technologies and robotics are both positively associated with subsequent investments in AI, only the former correlate positively with AI-related training, suggesting that workforce upskilling is less relevant when AI integration follows a substitution logic.

While these dynamics – of augmentation vs substitution – are often shaped by product, market, and industry characteristics, they do not imply technological destinies: firm behavior mediates their unfolding. To explore the role of both internal and external constraints, we provide additional evidence on the role of workforce engagement and sectoral heterogeneity.

Results show that firms offering employees welfare services beyond legal or contractual obligations are more likely to implement AI and invest in related training. Interaction terms indicate that the association is especially pronounced when AI is integrated with advanced information technologies, reinforcing the idea that worker engagement is particularly important in settings where AI

[1] That robots tend to substitute human input is largely established. Acemoglu and Restrepo (2020) argue that many automation technologies yield sizable displacement effects but modest productivity gains suggesting they are primarily introduced to reduce labor costs. Engineering studies support this view: robotic systems in construction are typically deployed to replace labor with minimal investment in workforce development (Liu *et al.* 2024).

complements – rather than substitutes – human input. This aligns well with a partial gift exchange logic à la Akerlof (1982), whereby high-performance work systems and management practices (Bloom *et al*. 2012; Appelbaum *et al.* 2000; Ichniowski *et al.* 1997) amplify the returns to technological upgrading. It also supports broader narratives on inclusive digitalization (OECD 2019), which emphasize the importance of workforce development to ensure that innovation yields shared productivity gains.

Yet, while organizational choices are pivotal in shaping the path towards AI, they do not unfold in an organizational vacuum, but within structural constraints. In manufacturing, where automation is more feasible, results indicate that all digital technologies – including robotics – correlate positively with AI adoption and AI-related training. In services, only advanced information technologies are significantly associated with AI adoption, and none correlate with AI-related training, suggesting that substitution logics are at least partly shaped by the nature of production.

Finally, while fiscal incentives are often framed as key drivers of technological change, our findings show that their effectiveness in Italy remains limited. In the full sample, firm access to Industry 4.0 incentives correlates with AI adoption – but this association disappears in the matched sample. This suggests that such policies primarily benefit firms that already had the internal capabilities to adopt AI. Once we compare firms with similar observable characteristics, in fact, incentives no longer appear to influence adoption or training outcomes. This raises concerns about the risk of widening existing digital divides: without complementary interventions to help lagging firms build foundational capabilities, these policies may reinforce, rather than reduce, between-firm inequalities.

The paper proceeds as follows. Section 2 presents the conceptual distinction that frames our interpretation of the empirical results against the background of the relevant literature. Section 3 describes the data used in the empirical analysis. Section 4 presents the econometric strategy and the empirical results. Section 5 concludes.

2. Background

2.1 Robots vs AIT

Attention to how AI integrates into technological systems has been growing (Venkatesh 2022). The role of existing human-machine interactions, however, remains largely unexplored. To address this gap, we develop a conceptual framework in which AI reinforces pre-existing technological dynamics – amplifying substitution when paired with robotics, and enhancing augmentation when combined with AIT.

Recent evidence from manufacturing, and construction indeed shows that AI interacts with robots through predictive automation and intelligent process loops that extend the substitution logic introduced by robotic capital (Adeyi *et al.* 2025; Chen *et al.* 2024). Acemoglu and Restrepo (2020) report that AI-induced reductions in machinery costs strengthen automation incentives and accelerate the shift toward machine-machine integration. In such settings, AI is often implemented with limited worker consultation or training (OECD 2023).

By contrast, when AI is combined with advanced information technologies, it operates within a human-machine complementarity framework, helping human operators leverage the full potential of data infrastructures by organizing and processing information at scale. Yet, integration requires training, as operators must learn to work with these tools. According to Hazan *et al.* (2024), firms adopting such systems are more likely to invest in internal upskilling, reflecting a logic of comparative advantage: while humans bring judgment, context, and ethical reasoning, AI excels at pattern recognition and data processing. These complementarities foster cognitive specialization and yield significant productivity gains (Hemmer *et al.* 2023). Indeed, Wilder *et al.* (2020) show that human-AI teams outperform either working alone when AI systems are designed to selectively seek human input. Qualitative evidence from data scientists confirms that collaboration, not substitution, is central to AI deployment in data-intensive domains (Wang *et al.* 2019).

2.2 AI technologies

Although AI adoption remains limited, its productivity potential is substantial (Czarnitzki *et al.* 2023). Understanding the factors that enable or constrain its diffusion is thus crucial. To date, adoption is highly polarized, with larger and more innovative firms significantly more likely to implement AI. Pre-existing digital capabilities, management practices, and workforce skills appear to play a central role in shaping these patterns.

Available firm-level evidence typically draws on three main sources of information: surveys with dedicated AI questions, job vacancy data, and patent records. Using survey data, Zolas *et al.* (2020) report that only 6.6% of U.S. firms used AI in 2018. For the same year, Czarnitzki *et al.* (2022) estimate a 5.8% adoption rate in Germany, showing concentration among large firms in knowledge-intensive industries. Cho and Song (2025) find a 9% share of adopters in Korea, documenting strong technological dependency on prior digital investments. In Italy, 6.2% of firms with more than ten employees reported using AI in at least one of seven possible applications in 2020, compared to an EU average of 8% (ISTAT 2021). Again, rates are higher in ICT-intensive sectors such as telecommunications and software.

While informative, survey data often offer limited insight into the depth or scale of AI adoption, and panel coverage is typically lacking. For this reason, researchers have also turned to job vacancy data. By tracking firms' evolving skill needs, these data allow the construction of proxies for AI exposure based on AI-related requirements in job ads. These indicators are then employed to analyze the impact of AI exposure on firm performance and employment outcomes. Acemoglu and Restrepo (2019b), for instance, show that AI exposure correlates with reduced overall hiring. But this aggregate trend may mask important compositional effects: several studies document a steady rise in demand for AI skills over the past decade (Alekseeva *et al.* 2021; Babina *et al.* 2024). However, job postings reflect intended rather than realized adoption and may capture expectations more than actual implementation.

Patent data offer a complementary perspective on the production of AI-related innovation. Clearly, these insights are useful for understanding the dynamics of AI knowledge generation, but shed less light on actual adoption. Yet, patterns of AI-related invention appear to be shaped by the same path-dependent logic that characterizes adoption – namely, a reliance on pre-existing capabilities and complementary assets. Agrawal *et al.* (2019) show that AI patents are disproportionately filed by firms with strong innovation capabilities, underscoring the role of complementary assets in shaping invention trajectories. Santarelli e*t al.* (2022) find that AI patents are concentrated in high-tech services, while robotics patents are more prevalent in manufacturing. Igna and Venturini (2022) similarly show that prior innovation activity significantly increases the likelihood of becoming an AI patentee, reinforcing the idea that continuity and path-dependency shape not only AI adoption but also its development. Webb (2019) links AI, robotics, and software patents to occupational exposure, showing that AI innovations disproportionately affect high-skill tasks, while robotics is more associated with routine and middle-skill jobs.

Calvino *et al.* (2022) combine firm-level financials, online content, job postings, and IP records for U.K. firms. They find that AI adopters are larger, more productive, and more likely to have developed prior digital capabilities. This multidimensional approach reinforces the view that AI adoption follows cumulative technological trajectories.

2.3 AI related training

Evidence on AI-related training remains limited, but increasingly shows that skills requirement for effective implementation depend on the nature of AI technologies and how they are integrated into existing organizational modes.

Shifts in skill demand are often inferred from online job advertisements, which offer granular insights. Alekseeva *et al.* (2021) find that roles involving AI frequently call for technical skills such as programming, statistical analysis, and data management, often coupled with broader competencies like problem-solving, communication, and project coordination. Yet, explicit emphasis on advanced AI expertise remains rare. Bessen (2019), for instance, report that the majority of firms (around 59%) prioritize general computer literacy, while only a small fraction (10%) specifically require coding or data science skills. Moreover, while AI can replicate some cognitive skills, many occupations rely on abilities that are still challenging to automate, such as complex problem-solving and social skills (Lassébie and Quintini 2022). Altogether, this suggests that training for specialized AI skills likely requires a combination of both technology-specific and general skills, emphasizing the need to better fine-tune formal higher education and on-the-job learning.

The depth of integration matters. Standard AI tools – such as software for automating document review or customer support – can often be adopted with minimal internal adjustment, requiring only basic digital familiarity. In contrast, more complex applications—like predictive maintenance systems or AI-driven supply chain optimization – typically require significant adaptation of internal processes and greater coordination across teams (Lane e Saint-Martin 2023).

In these cases, hiring is not the only mechanism for acquiring the necessary skills. Firm-sponsored training – ranging from vendor-led introductions and short workshops to structured internal programs – is often used to build relevant capabilities. According to the OECD AI survey, between 64% and 71% of manufacturing firms that adopted AI offered some form of training to their workforce (Lane *et al.* 2023).

Still, training barriers remain. Firms often lack the resources, organizational bandwidth, or managerial expertise needed to assess training needs and coordinate programs effectively. Even firms equipped with data-generating processes and digital infrastructures may struggle to turn data into actionable insights (Lane e Saint-Martin 2023).

Available evidence also shows that the provision – and modalities – of AI-related training depend on sectoral and organizational conditions. In services, for example, training tends to be less structured due to operational constraints and institutional features. Many service activities involve simultaneous production and delivery (e.g., a retail assistant or a healthcare provider), where pulling workers out for formal training can disrupt frontline operations. Tasks are also more heterogeneous, making it harder to standardize training content. Moreover, service firms are often decentralized and dispersed across units, limiting economies of scale and coordination in skill development. HR decisions may be taken locally, hindering coherent firm-wide strategies. As a result, learning tends to occur informally, through on-the-job adaptation to AI tools – a pattern documented for Italy by Vermeulen *et al.* (2020) and supported more broadly by Wang *et al.* (2019) and OECD (2023).

Collective bargaining institutions also matter. In Italy – the country we analyze empirically – second-level agreements are for instance more widespread in industry than in services (Labartino *et al.* 2024). According to Berton *et al.* (2023), such agreements increase the likelihood that firms will adopt structured approaches to skill development. Altogether, these insights suggest that even when firms adopt AI, their ability to invest in complementary training is shaped by structural and institutional constraints – echoing the view that AI-human complementarity is not technologically determined but organizationally and contextually mediated (Wang *et al.* 2019; OECD 2023).

3. Data and Descriptive Statistics

3.1 Data

Our empirical analysis draws on firm-level data from the Rilevazione Imprese e Lavoro (RIL) survey, conducted by the Italian National Institute for Public Policy Analysis (INAPP) in 2018 and 2022. The survey covers a representative sample of partnership and limited liability firms in Italy's private, non-agricultural sectors. Approximately 45% of firms surveyed in 2022 also participated in the 2018 wave, enabling longitudinal analysis.

RIL collects useful information on top managers' characteristics (education, age, gender) and family-ownership, allowing to control for managerial characteristics that often drive unobserved heterogeneity in firm-level analyses. Moreover, it provides information on workforce composition and industrial relations (e.g., the distribution of employees by education, occupational status, gender, and contract type), as well as on a broad set of firms' characteristics (firm size, sales per employee, export share, and firm age) that measure their competitiveness and performance.

Crucially, the survey records whether firms invested in specific digital technologies – including AI– and whether they organized training activities related to such technologies. In the 2022 wave, firms were explicitly asked whether they had adopted selected digital technologies between 2019 and 2021, including AI, big data, IoT/AR, robotics, and cloud computing. Firms that reported offering training programs in 2021 were further asked whether these were related to enabling technologies associated with the so-called Industry 4.0. A follow-up question identified the specific technologies addressed, such as AI, collaborative robotics, and augmented or virtual reality.

The survey also provides data on firms' access to fiscal incentives introduced under Italy's Industry Plan 4.0, a policy initiative aimed at reducing financial constraints on technological investment and fostering the adoption of advanced digital technologies.

Finally, the survey records whether firms provide welfare services to employees beyond legal or contractual obligation – including parental leave and childcare, health and pension benefits, family allowances, and fringe benefits. These practices fall within the broader category of occupational welfare, referring to employer-driven initiatives to support workers' well-being beyond statutory requirements. As discussed by Natali and Pavolini (2018), such practices have become increasingly relevant across European labor markets, especially in contexts where public welfare provision is limited and firms seek to enhance employee retention and motivation through private initiatives. The variables' description is summarized in Table 1.

Table 1. Variables definition

	Technology
AI tech	A dummy $= 1$ if the firm invested in AI during 2019-2021.
AI related training	A dummy $= 1$ if the firm invested in AI-related training in 2021.
Digital tech	A dummy $= 1$ if the firm adopted at least one digital technology (IoT, big data analytics, augmented reality, robotics) during 2015-2017; 0 otherwise.
Information tech	A dummy $= 1$ if the firm adopted at least one information technology (IoT, big data analytics, augmented reality) during 2015-2017.
Robotics	A dummy $= 1$ if the firm invested in robotics during 2015-2017.
	Management characteristics
Manager's education	A dummy $= 1$ if the top manager is tertiary educated.
Manager's age	Top manager's age (in years).
Manager's female	A dummy $= 1$ if the top manager is female.
Family ownership	A dummy $= 1$ if the firm is family-owned.
	Workforce characteristics
Education	% of employees with i) tertiary education; ii) upper-secondary education; iii) lower-secondary education.
Professional status	% of: i) executives, ii) white collars, and iii) blue collars.
Female	% of female workers.
Fixed term	% of fixed term contracts.
	Firm characteristics
Welfare services	A dummy $= 1$if the firm provides/finances employee welfare services (maternity leaves and childcare, health care, private pension funds, current family expenditures, other firing benefits).
Tax incentives	A dummy $= 1$ if the firm used at least one fiscal incentive for investments in 2017 (Hyper and super depreciation; tax credit for R&D expenditures; "New Sabatini" Tax credit for I4.0 training; startup and SME innovative enterprises, Patent box, other).
Foreign markets	A dummy $= 1$ if the firm sells in international markets.
Firm's performance	(Log of) total deflated sales in euros per employee.
Firm's size	(Log of) number of employees
Firm's age	(Log of) number of years since the firm's foundation.
Location	20 dummy variables indicating the Italian NUTS2 regions.
Sector	16 dummy variables indicating non-agricultural 2-digit ATECO (Italian National Institute of Statistics, ISTAT).

Source: RIL Data

We restrict the sample to firms with at least nine employees. Excluding micro-firms, which typically lack developed organizational routines, is appropriate when analyzing investment in advanced digital technologies. After excluding observations with missing values on key variables, the final longitudinal sample includes approximately 7,000 firms. This allows us to examine whether prior adoption of advanced information technologies and robotics correlates positively with subsequent investment in AI and related training, while controlling for relevant firm characteristics.

3.2 Descriptive Statistics

Table 2 presents descriptive statistics. Between 2019 and 2021, only 1.3% of firms invested in AI technologies, and fewer than 1% invested in AI-related training[2]. By contrast, advanced digital technology adoption was more common in the earlier period: 19% of firms had adopted at least one advanced digital technology between 2015 and 2017, 15.3% had adopted at least one advanced information technology (IoT, big data, or AR), and 6% had invested in robotics. These figures are consistent with the patterns documented by Cirillo *et al.* (2023), who show that technological upgrading among Italian firms is highly uneven and strongly conditioned by firms' human capital and digital infrastructure (ICT, cybersecurity, and data management) which together constitute the technological and organizational foundations requires to support more advanced digitalization. As a result, most firms initially focus on foundational investments, postponing the adoption of more complex technologies like AI or robotics until complementary capabilities are in place.

Descriptive statistics on management characteristics show that 28% of firms were led by a university graduate, 13.5% by a woman, and that the average top manager was about 57 years old. The low incidence of graduate and female managers may reflect the intergenerational control typical of family-owned firms, which account for 85 % of our sample. As widely documented, family firms are often characterized by managerial profiles oriented toward conservatism and the preservation of socioemotional wealth, prioritizing non-economic goals such as family legacy and control at the expense of high-risk investment decisions (Souder *et al.* 2017; Gómez-Mejía *et al.* 2007; Berrone *et al.* 2012). This conservative orientation, in turn, may explain their lower propensity to invest in digital technologies, as recently shown by Basiglio *et al.* (2025).

The workforce profile indicates relatively low levels of formal education: only 13.5% of employees held a university degree, and just 4.2% held executive roles. Moreover, 34% of workers were women, and around 17.6% had temporary contracts.

Additional firm-level indicators show that 13.8% of firms used at least one fiscal incentive linked to Italy's Industry 4.0 Plan; 3.5% provided employee welfare services beyond contractual obligations; 36% operated in manufacturing; and 81% were located in the Centre-North. On average, 37% of total sales came from international markets.

[2] The share of AI adopters recorded by ISTAT over the same period is around 6.4 %. Such difference may be explained by the fact that ISTAT collects information on firms that *use* AI, while RIL explicitly ask firms if they *invest* in such technology.

Table 2. Descriptive statistics

	Mean	Std dev	Min	Max
	investment and technologies			
AI tech	0,013	0,115	0	1
AI training	0,009	0,094	0	1
Digital tech	0,190	0,393	0	1
Information tech	0,153	0,360	0	1
Robotics	0,060	0,238	0	1
	management characteristics			
Tertiary ed	0,279	0,448	0	1
Firm age (in years)	56,73	11,46	20	80
Female	0,135	0,342	0	1
Family ownership	0,852	0,354	0	1
	workforce characteristics			
Share of executives	0,042	0,095	0	1
Share of white collars	0,361	0,304	0	1
Share of blue collars	0,597	0,325	0	1
Share of female	0,340	0,254	0	1
Share of temporary	0,176	0,236	0	1
Share of graduated	0,135	0,211	0	1
Share of upper secondary	0,487	0,290	0	1
Share of lower ed	0,378	0,319	0	1
	workforce characteristics			
Fiscal incentive	0,138	0,345	0	1
Firm provided welfare	0,035	0,183	0	1
Share of sales foreign mkt	0,369	0,483	0	1
Ln (firm age)	3,15	0,693	0	5,25
Ln (n of employees)	3,11	0,846	2,30	9,29
Ln (sales per employee)	11,8	1,27	6,11	15,2
Manufacturing	0,36	0,481	0	1
Centre-North	0,810	0,392	0	1
N of Obs.		7.168		

Notes: longitudinal sampling weights applied. All control variables are computed on RIL 2018.
Source: authors' elaborations on RIL longitudinal sample 2018-2021

The correlation matrix in Table 3 reveals a distinct asymmetry in how different technologies relate to AI adoption and training. AI investment is positively correlated with both robotics and information technologies, although the correlation with information technologies (0.086) is slightly stronger. By contrast, AI-related training shows a meaningful correlation only with information technologies (0.072), and virtually none with robotics (0.002). This pattern reinforces our interpretation that AI deployment reflects diverging technological trajectories depending on existing human-technology relationships.

Table 3. Correlation matrix

	AI tech	AI training	Inf Tech	Robotics
	whole sample			
AI tech	1			
AI training	0,144	1		
Information tech	0,086	0,0716	1	
Robotics	0,073	0,0024	0,1639	1
	welfare services			
AI tech	1			
AI training	0,383	1		
Information Tech	0,158	0,201	1	
Robotics	0,067	0,004	0,241	1
	No welfare services			
AI tech	1			
AI training	0,096	1		
Information Tech	0,072	0,053	1	
Robotics	0,074	0,001	0,159	1

Notes: longitudinal sampling weights applied.
Source: authors' elaborations on RIL longitudinal sample 2018-2021

The organizational context further qualifies these differences. Correlations between AI-related training and prior technologies are generally stronger among firms that offer employee welfare services beyond legal or contractual obligations. In these firms, AI-related training is more strongly associated with information technologies (0.201), while the correlation with robotics remains negligible (0.004). These patterns are consistent with a partial gift exchange logic (Akerlof 1982), whereby organizational investments in employee well-being foster engagement and support more inclusive digitalization – enhancing the returns to training and skill development.

4. Empirical analysis

4.1 Econometric strategy

Equation (1) models the probability that a firm invests in AI or in AI-related training as a (linear) function of prior digital investments and other firm-level controls. Our baseline specification is:

$$A_{i,t+1} = \beta_0 + \beta_1 T_{i,t} + \beta_2 V_{i,t} + \beta_3 S_{i,t} + \beta_4 M_{i,t} + \beta_5 W_{i,t} + \beta_6 F_{i,t} + \lambda_r + \mu_s + \varepsilon_{i,t}, \tag{1}$$

where $A_{i,t+1}$ is a binary variable indicating whether firm i invested in AI between 2019-2021, or in AI-related training in 2021; $T_{i,t} \in \{D_{i,t}, I_{i,t}, R_{i,t}\}$ is our main regressor of interest, where $D_{i,t}$ is a binary variable indicating whether firm i adopted at least one advanced digital technology (IoT, big data analytics, augmented reality, robotics) over the period 2015-2017; $I_{i,t}$ is a binary variable indicating whether firm i adopted at least one advanced information technology (IoT, big data analytics, augmented reality) over the period 2015-2017; and $R_{i,t}$ is a binary variable indicating whether firm i invested in robotic capital over the period 2015-2017. $V_{i,t}$, in turn, is a dummy that records the use of at least one fiscal incentive under Italy's Industry 4.0 Plan; while $S_{i,t}$ is a dummy indicating whether firm i offered at least one welfare service beyond legal or contractual obligations (e.g., subsidized childcare, health benefits, or complementary pension). Finally, $M_{i,t}$, $W_{i,t}$, and $F_{i,t}$ are vectors for management characteristics, workforce composition, and firm-level structural variables, respectively; while λ_r, and μ_s are region (NUTS2) and sector fixed effects; and $\varepsilon_{i,t}$ is an idiosyncratic error term.

We estimate equation (1) using probit models, and report average marginal effects (AMEs) in Tables 4 and 5, for AI investments and AI-related training, respectively. The wide array of controls allows us to account for a rich set of observable and, to some extent, unobservable characteristics, mitigating concerns about omitted variable bias and simultaneity[3].

Still, concerns about endogeneity remain. Firms that adopted digital technologies between 2015 and 2017 may differ from non-adopters in unobservable ways – for instance, in long-term innovation orientation or managerial foresight. This concern is especially relevant given the lack of detailed information on past R&D investments, patent portfolios, or broader innovation strategies. Such unobservables likely reflect elements of firm culture and routines that shape technology adoption over time (Nelson and Winter 1982).

To address this issue, we complement our regressions with propensity score matching (PSM). Specifically, we estimate the likelihood of adopting each digital technology in 2015-2017 based on firms' pre-treatment characteristics and match treated and control firms within the common support. This helps mitigate selection bias on observables and provides a robustness check that does not rely on functional form assumptions.

To assess the quality of the matching procedure, we compare the mean values of a broad set of covariates between treated and control groups. Tables 4 and 5 report the results of PSM balancing tests for our two main regressions (AI adoption and AI-related training, respectively). The results confirm that, after matching, there are no statistically significant differences in observed covariates between treated and control firms. Only two covariates – welfare services and foreign markets – do not reach conventional significance at the 5% level. This evidence alleviates concerns about selection on observables and strengthens the internal consistency of our empirical approach[4].

[3] We also run linear regression models to estimate equation (1). Ols coefficient are coherent with our preferred probit estimates of the average marginal effects. Linear estimates are available upon request.

[4] For reasons of space, we do not report balancing statistics for the robustness regressions. Results are available from the authors upon request.

Table 4. P-value of the test of balanced covariates after matching. Treatment: Digital Technologies. Dep var: AI technologies

	Matched	Treated	Control	% bias	% reduct bias	t	$p > t$
Fiscal incentives	U	0,265	0,143	30,8		12,61	0,000
	M	0,264	0,270	-1,4	95,4	-0,42	0,677
Manager: graduated	U	0,467	0,360	21,8		8,56	0,000
	M	0,466	0,467	-0,2	99,1	-0,06	0,951
Manager: age	U	57,48	57,20	2,4		0,95	0,344
	M	57,48	57,31	1,5	37,9	0,51	0,611
Manager: female	U	0,092	0,119	-8,8		-3,34	0,001
	M	0,093	0,084	2,8	68,6	0,97	0,330
Family owner	U	0,628	0,744	-25,2		-10,04	0,000
	M	0,629	0,626	0,5	98,0	0,16	0,874
Share of executives	U	0,059	0,042	18,1		7,13	0,000
	M	0,059	0,061	-2,8	84,8	-0,82	0,412
Share of white collars	U	0,404	0,361	14,7		5,68	0,000
	M	0,403	0,414	-3,8	74,1	-1,24	0,215
Share of female	U	0,306	0,308	-1,2		-0,46	0,645
	M	0,306	0,306	0,2	85,3	0,06	0,951
Share of FT	U	0,127	0,142	-8,8		-3,35	0,001
	M	0,126	0,134	-4,1	53,2	-1,35	0,176
Share of graduated	U	0,215	0,153	27,2		10,78	0,000
	M	0,214	0,213	0,1	99,7	0,02	0,983
Share of upper secondary	U	0,462	0,465	-1,0		-0,38	0,707
	M	0,463	0,471	-3,0	-207,1	-1,04	0,298
Foreign markets	U	0,604	0,365	49,2		19,18	0,000
	M	0,604	0,580	4,9	90,1	1,56	0,118
ln (firm age)	U	3,31	3,23	13,1		5,08	0,000
	M	3,31	3,29	3,8	70,9	1,25	0,213
Welfare services	U	0,118	0,048	25,7		10,96	0,000
	M	0,117	0,099	6,6	74,5	1,88	0,060
ln (n of employee)	U	4,565	3,80	65,5		26,28	0,000
	M	4,555	4,58	-2,1	96,8	-0,63	0,530
ln (sales per employee)	U	12,07	11,84	17,4		6,78	0,000
	M	12,08	12,02	3,4	80,5	1,05	0,292

Notes: other controls are omitted for saving space * if variance ratio outside [0.88; 1.14] for U and [0.88; 1.14] for M.
Source: authors' elaborations on RIL data

Table 5. P-value of the test of balanced covariates after matching. Treatment: Digital Technologies. Dep var: AI related training

	Matched	Treated	Control	% bias	% reduct bias	t	$p > t$
Fiscal incentives	U	0,265	0,143	30,8		12,61	0,000
	M	0,264	0,270	-1,4	95,4	-0,42	0,677
Manager: graduated	U	0,467	0,360	21,8		8,56	0,000
	M	0,466	0,467	-0,2	99,1	-0,06	0,951
Manager: age	U	57,48	57,20	2,4		0,95	0,344
	M	57,48	57,31	1,5	37,9	0,51	0,611
Manager: female	U	0,092	0,119	-8,8		-3,34	0,001
	M	0,093	0,084	2,8	68,6	0,97	0,330
Family owner	U	0,628	0,744	-25,2		-10,04	0,000
	M	0,629	0,626	0,5	98,0	0,16	0,874
Share of executives	U	0,058	0,042	18,1		7,13	0,000
	M	0,059	0,061	-2,8	84,8	-0,82	0,412
Share of white collars	U	0,404	0,361	14,7		5,68	0,000
	M	0,403	0,414	-3,8	74,1	-1,24	0,215
Share of female	U	0,306	0,308	-1,2		-0,46	0,645
	M	0,306	0,305	0,2	85,3	0,06	0,951
Share of FT	U	0,127	0,142	-8,8		-3,35	0,001
	M	0,127	0,134	-4,1	53,2	-1,35	0,176
Share of graduated	U	0,215	0,153	27,2		10,78	0,000
	M	0,213	0,213	0,1	99,7	0,02	0,983
Share of upper secondary	U	0,462	0,464	-1,0		-0,38	0,707
	M	0,462	0,470	-3,0	-207,1	-1,04	0,298
Foreign markets	U	0,604	0,366	49,2		19,18	0,000
	M	0,604	0,580	4,9	90,1	1,56	0,118
ln (firm age)	U	3,31	3,22	13,1		5,08	0,000
	M	3,31	3,29	3,8	70,9	1,25	0,213
Welfare services	U	0,118	0,048	25,7		10,96	0,000
	M	0,117	0,098	6,6	74,5	1,88	0,060
ln (n of employee)	U	4,56	3,81	65,5		26,28	0,000
	M	4,55	4,58	-2,1	96,8	-0,63	0,530
ln (sales per employee)	U	12,07	11,84	17,4		6,78	0,000
	M	12,07	12,02	3,4	80,5	1,05	0,292

Notes: other controls are omitted for saving space * if variance ratio outside [0.88; 1.14] for U and [0.88; 1.14] for M.
Source: authors' elaborations on RIL data

Despite endogeneity concerns are not fully ruled out, the timing of adoption – digital technologies in 2015-2017 and AI after 2019 – supports a sequential interpretation. Moreover, pre-trends are unlikely to drive results: AI adoption remained extremely limited before 2019, due to supply-side constraints and firms' limited absorptive capacity. Indeed, the barriers already discussed – underdeveloped data management, lack of skilled personnel, and weak digital infrastructure – were likely even more pronounced before 2019.

4.2 Main Results: AI technologies

Table 6 presents average marginal effects (AMEs) from probit regressions where the dependent variable is the probability of investing in AI. The first three columns report estimates based on the full sample and separately consider our three main regressors: digital technologies overall (column 1), information technologies (column 2), and robotics (column 3). All coefficients are positive and statistically significant, with AMEs ranging from +1.5% to +1.8%. This suggests that prior adoption of digital technologies – whether oriented toward information processing or automation, is associated with an increased likelihood of subsequent AI investment.

Table 6. Probit estimates AME. Dep var: AI Technologies 2019-2021

	whole sample			matched sample		
	[1]	[2]	[3]	[4]	[5]	[6]
Digital tech	0,015***			0,024***		
	(0,004)			(0,009)		
Information tech		0,018***			0,036***	
		(0,004)			(0,008)	
Robotics			0,018***			0,034***
			(0,006)			(0,012)
Tax incentive	0,009*	0,009*	0,010**	0,046***	0,020**	0,019
	(0,005)	(0,005)	(0,005)	(0,012)	(0,010)	(0,013)
Welfare services	0,020***	0,020***	0,021***	0,029**	0,018*	0,045***
	(0,006)	(0,006)	(0,006)	(0,012)	(0,011)	(0,017)
ln (n. of employees)	0,014***	0,014***	0,014***	0,019***	0,017***	0,020***
	(0,002)	(0,002)	(0,002)	(0,004)	(0,003)	(0,007)
ln (sales per empl)	0,004*	0,004**	0,004*	0,006*	0,002	0,005
	(0,002)	(0,002)	(0,002)	(0,004)	(0,004)	(0,005)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
N of Obs.	7399	7399	7399	3392	2918	1399

Notes: management characteristics by education, age, gender, presence of family management; workforce composition by education, professional status, contractual arrangements, gender; firms' characteristics include indicator for selling products and services on foreign markets, firms age (in years), (log of) the number of employees, nuts 2 regions, sectors of activities (OECD classification). Standard errors (clustered at the firm level) are in parentheses. *** at 1%, ** 5%, * 1%.
Source: authors' elaborations on RIL longitudinal data

Columns 4 to 6 replicate these estimates on the matched sample obtained with the PSM procedure. The results are stronger in magnitude: +2.4% for digital technologies overall, +3.6% for information technologies, and +3.4% for robotics. These results emphasize the role of prior digital adoption in shaping subsequent AI implementation, especially among firms with similar ex-ante characteristics. The larger marginal effects in the matched sample indeed suggest that, once we control observable differences, the relationship between earlier digitalization and later AI investment becomes even more pronounced.

All other variables behave as expected. The provision of employee welfare services are positively associated with AI investment throughout all specifications, consistent with the idea that high-performance work practices support technological upgrading by fostering trust and engagement. Importantly, the correlation with fiscal incentives is statistically significant only in the matched sample, suggesting that such policies are most effective among firms that had already developed the internal capabilities required to adopt AI.

4.3 Main Results: AI-related training

Table 7 reports average marginal effects (AMEs) from probit regressions where the dependent variable is whether the firm invested in AI-related training in 2021. In the full sample, all advanced digital technologies show weak or non-significant associations with training investments. The AMEs are +0.6% for both digital and information technologies, and +0.4% for robotics, but only the first two are statistically significant at the 5% level.

Table 7. Probit estimates AME. Dep var: AI-related training 2021

	whole sample			matched sample		
	[1]	[2]	[3]	[4]	[5]	[6]
Digital tech	0,006**			0,012**		
	(0,003)			(0,005)		
Information tech		0,006**			0,016***	
		(0,003)			(0,006)	
Robotics			0,004			0,013
			(0,004)			(0,010)
Tax incentive	0,008**	0,008**	0,008**	0,009	0,003	0,006
	(0,003)	(0,003)	(0,003)	(0,006)	(0,006)	(0,010)
Welfare services	0,016***	0,016***	0,016***	0,021***	0,027***	0,030**
	(0,004)	(0,004)	(0,004)	(0,006)	(0,007)	(0,013)
ln (n of employees)	0,008***	0,008***	0,008***	0,010***	0,010***	0,020***
	(0,001)	(0,001)	(0,001)	(0,003)	(0,003)	(0,006)
ln (sales per empl)	0,001	0,001	0,001	0,002	0,001	-0,003
	(0,001)	(0,001)	(0,001)	(0,003)	(0,003)	(0,004)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
N of Obs.	6792	6792	6792	3216	2714	1168

Notes: management characteristics by education, age, gender, presence of family management; workforce composition by education, professional status, contractual arrangements, gender; firms' characteristics include indicator for selling products and services on foreign markets, firms age (in years), (log of) the number of employees, nuts 2 regions, sectors of activities (OECD classification). Standard errors (clustered at the firm level) are in parentheses. *** at 1%, ** 5%, * 1%.
Source: authors' elaborations on RIL longitudinal data

In the matched sample, the estimated marginal effects increase. Information technologies show the strongest association with AI-related training (+1.6%), followed by overall digital adoption (+1.2%), while the effect of robotics remains small and not statistically significant (+1.3%). These results support our interpretation that AI-related training is more closely linked to prior adoption of information technologies – where human-machine complementarity and upskilling are more salient – than to robotics – which tends to reflect a substitution-oriented path.

A similar pattern emerges in Table 8, which considers digital training not specifically targeted at AI. Also here, robotics shows no significant correlation, whereas digital and information technologies are both associated with broader training investments. Even general upskilling appears to follow trajectories in which technologies are integrated into work processes in ways that rely on human input – supporting our distinction between substitution – and augmentation-based paths of technological upgrading.

Table 8. Probit estimates AME. Dep var: digital Training (excluding AI) 2021

	whole sample			*matched sample*		
	[1]	[2]	[3]	[4]	[5]	[6]
Digital tech	0,024***			0,029***		
	(0,007)			(0,011)		
Information tech		0,023***			0,036***	
		(0,007)			(0,011)	
Robotics			0,019**			0,003
			(0,009)			(0,019)
Tax incentive	0,036***	0,037***	0,038***	0,054***	0,034***	0,061***
	(0,007)	(0,007)	(0,007)	(0,012)	(0,012)	(0,020)
Welfare services	0,023*	0,022*	0,024**	0,016	0,022	0,034
	(0,012)	(0,012)	(0,012)	(0,017)	(0,017)	(0,029)
N of Obs.	7371	7371	7371	3425	2917	1436

Notes: management characteristics by education, age, gender, presence of family management; workforce composition by education, professional status, contractual arrangements, gender; firms' characteristics include indicator for selling products and services on foreign markets, firms age (in years), (log of) the number of employees, nuts 2 regions, sectors of activities (OECD classification). Standard errors (clustered at the firm level) are in parentheses. *** at 1%, ** 5%, * 1%.
Source: authors' elaborations on RIL longitudinal data

The other coefficients in Table 7 have the expected sign. Again, firms offering non-compulsory employee welfare services are more likely to invest in AI-related training. Differently for the estimates in Table 6, fiscal incentives do not appear to promote AI-related training – even among firms that are ex-ante comparable in terms of observable capabilities. Hence, whatever association emerges in the full sample is explained by selection, and disappears once we control for firm characteristics. This contrast suggests that while incentives may support adoption among already capable firms, they are insufficient to trigger firm-sponsored training, which likely depends on deeper organizational commitments beyond technical readiness.

4.4 Further evidence: the welfare services and sectoral heterogeneity

To further explore the role of organizational practices in shaping technological and skill upgrading, we examine whether the presence of employee welfare services strengthens the relationship between past digital adoption and subsequent investments in AI technologies and related training. To do so, we augment equation (1) with a set of interaction terms, $\beta_7 T_{i,t} \times W_{i,t}$, capturing how the effect of digital adoption $T_{i,t}$ varies with the provision of welfare services $W_{i,t}$. This specification allows us to assess whether the association between past digital adoption and AI outcomes is stronger among firms that provide such services. Table 9 reports average marginal effects from probit models estimated on both the full and matched samples: While results are broadly consistent across specifications, we focus our discussion on the matched sample, which offers a cleaner comparison by conditioning on pre-treatment characteristics.

Table 9. Probit estimates AME w. technology/welfare interactions

	whole sample			matched sample		
	[1]	[2]	[3]	[4]	[5]	[6]
	Panel A: AI Technologies					
Digital tech=No	0,027**			0,031		
	(0,013)			(0,025)		
Digital tech=Yes	0,026*			0,039**		
	(0,014)			(0,019)		
Information tech=No		0,024**			0,009	
		(0,012)			(0,016)	
Information tech=Yes		0,030*			0,031*	
		(0,015)			(0,020)	
Robotics=No			0,023**			0,054
			(0,010)			(0,034)
Robotics=Yes			0,044*			0,054
			(0,025)			(0,033)
N of Obs.	7399	7399	7399	3392	2918	1399
	Panel B: AI-related training					
Digital tech=No	0,001			-0,009		
	(0,007)			(0,008)		
Digital tech=Yes	0,042***			0,056***		
	(0,012)			(0,016)		
Information tech=No		0,005			0,011	
		(0,007)			(0,014)	
Information tech=Yes		0,042***			0,061***	
		(0,013)			(0,018)	
Robotics=No			0,020***			0,024
			(0,008)			(0,026)
Robotics=Yes			0,034**			0,053*
			(0,017)			(0,028)
N of Obs.	6792	6792	6792	3216	2714	1168

Notes: management characteristics by education, age, gender, presence of family management; workforce composition by education, professional status, contractual arrangements, gender; firms' characteristics include indicator for selling products and services on foreign markets, firms age (in years), (log of) the number of employees, nuts 2 regions, sectors of activities (OECD classification). Standard errors (clustered at the firm level) are in parentheses. *** at 1%, ** 5%, * 1%.
Source: authors' elaborations on RIL longitudinal data

Panel A shows that among firms offering welfare services, the likelihood of AI investments increases significantly when digital technologies were previously adopted (+3.9 p.p.), while no significant effect emerges in firms that did not adopt such technologies. The effect is slightly more pronounced for information technologies than for robotics, suggesting that welfare services are particularly relevant when AI builds on technologies that complement – not substitute – human input. While worker disengagement may generally fuel resistance to technological change, motivation plays an especially pivotal role when AI is used to enhance the performance of employees operating advanced information technologies in cognitively demanding tasks. In these contexts, the effectiveness of human-AI complementarity depends more strongly on labor effort and worker motivation.
Panel B presents estimates for AI-related training. Here, the pattern is even stronger: the presence of welfare services significantly amplifies the positive association between digital adoption and training

investments. Marginal effects rise to +5.6 p.p. for digital technologies overall, and are similarly high for both information technologies (+6.1 p.p.) and robotics (+5.3 p.p.).
Interestingly, the presence of welfare services also strengthens the relationship between robotics and AI-related training. While this might initially seem at odds with the view that robotics tends to substitute for labor rather than complement it, we interpret this as further evidence of organizational mediation. In firms that invest in employee well-being, even automation-oriented technologies can be integrated into broader strategies of workforce development. This echoes recent findings that even labor-substituting technologies like robotics can be embedded in worker-centered implementations when supported by inclusive organizational practices (OECD 2023; Acemoglu and Restrepo 2019b). As such, the boundary between substitution and augmentation is not technologically fixed but organizationally contingent (Vermeulen *et al.* 2020; Wang *et al.* 2019).

Table 10. Probit estimates AME industry/services (matched sample only)

	Industry			*Services*		
	[1]	[2]	[3]	[4]	[5]	[6]
	Panel A: AI technologies					
Digital tech	0,013**			0,018***		
	(0,006)			(0,007)		
Information tech		0,015***			0,021***	
		(0,005)			(0,007)	
Robotics			0,021***			0,011
			(0,006)			(0,013)
Tax incentive	0,011*	0,011**	0,011*	0,004	0,004	0,005
	(0,006)	(0,006)	(0,006)	(0,009)	(0,009)	(0,009)
Welfare services	0,017**	0,016*	0,017**	0,026***	0,026***	0,027***
	(0,008)	(0,008)	(0,008)	(0,009)	(0,009)	(0,009)
N of Obs.	4228	4228	4228	3083	3083	3083
	Panel B: AI related training					
Digital tech	0,007*			0,003		
	(0,004)			(0,005)		
Information tech		0,006*			0,003	
		(0,004)			(0,005)	
Robotics			0,003			0,009
			(0,004)			(0,008)
Tax incentive	0,005	0,005	0,005	0,014**	0,014**	0,014**
	(0,004)	(0,004)	(0,004)	(0,006)	(0,006)	(0,006)
Welfare services	0,014***	0,014***	0,015***	0,020***	0,020***	0,020***
	(0,005)	(0,005)	(0,005)	(0,006)	(0,006)	(0,007)
N of Obs.	3674	3674	3674	2732	2732	2732

Notes: management characteristics by education, age, gender, presence of family management; workforce composition by education, professional status, contractual arrangements, gender; firms' characteristics include indicator for selling products and services on foreign markets, firms age (in years), (log of) the number of employees, nuts 2 regions, sectors of activities (OECD classification). Standard errors (clustered at the firm level) are in parentheses. *** at 1%, ** 5%, * 1%.
Source: authors' elaborations on RIL longitudinal data

Yet, the productive context does play a role in shaping how these dynamics unfold. Estimates from Table 10 – based on the matched sample – show that past investments in all digital technologies, including robotics, are positively associated with subsequent AI adoption in industry. In services, by contrast, only information technologies exhibit a significant correlation. That AI complements robotics in settings where task automation is more feasible, while it enhances human input in contexts where data infrastructures support cognitively demanding tasks, reinforces the idea that AI integration follows distinct logics depending on the productive context in which it is applied.

Interestingly, tax incentives significantly correlate with AI adoption only in industry, possibly suggesting that external policy levers accelerate automation-related investment in sectors where capital-labor substitution is likely more viable. By contrast, in services, where AI applications often rely on human-machine complementarity, adoption seems to depend more on endogenous organizational capabilities than on exogenous incentives.

Panel B reveals a similar contrast with respect to AI-related training. In industry, only information technologies are positively associated with subsequent training investments. This supports our interpretation that training is particularly important when AI is deployed following a human-machine augmentation logic in which proper upskilling is pivotal. In services, however, no significant link emerges between past investments in any type of advanced digital technology and AI-related training – a pattern consistent with prior evidence that formal upskilling is less prevalent in services, where decentralized structures, task heterogeneity, and delivery-side constraints make training more difficult to implement (see Section 2.3, p.7; OECD 2019).

5. Conclusions

This paper provides new evidence on the role of technological path-dependency in shaping firms' investments in AI and AI-related training. Using a rich longitudinal dataset of Italian firms, it shows that earlier investments in all types of advanced digital technologies correlate positively with subsequent AI adoption. Yet only advanced information technologies such as big data are associated with AI-related training.

The paper rationalizes these results by arguing that these patterns reflect different modes of integrating AI into existing techno-organizational systems. While robotics tends to support a machine–machine logic focused on substitution, advanced information technologies enable human–machine complementarity and cognitive augmentation. AI, we argue, both follows and reinforces these human-technology interactions, explaining why only advanced information technologies are associated with upskilling investments.

Moreover, results show that employee welfare services correlate positively with both AI and training investment, suggesting that worker engagement facilitates digital upgrading. In contrast, fiscal incentives appear to benefit only those firms that had already accumulated the capabilities needed to adopt AI, raising concerns about their potential impact in widening existing digital divides and productivity gaps.

These findings speak to a range of established theoretical perspectives. While the differentiated role of digital technologies supports the idea of technology-skill complementarities (Autor *et al.* 2003; Brynjolfsson and McElheran 2016), the cumulative nature of adoption paths aligns with theories of capability building and organizational routines (Nelson and Winter 1982; Dosi *et al.* 2000), as well as with the concept of absorptive capacity – the idea that firms must build prior knowledge to effectively recognize, assimilate, and apply new technologies (Cohen and Levinthal 1990). Likewise, the association between workforce engagement and technological upgrading echoes the literature on high-performance work systems and worker involvement in innovation (Appelbaum *et al.* 2000; Ichniowski *et al.* 1997). In this sense, the paper not only fills an empirical gap but also contributes to refining existing frameworks in the context of AI.

Altogether, these results reinforce the view that AI adoption is but a stage in a broader, cumulative process of technological upgrading – one shaped by firms' prior digital investments and accumulated organizational capabilities. This differentiated path-dependency highlights how the nature of existing technology-human interactions – of substitution or augmentation – shapes not just AI adoption, but also firms' willingness to invest in related human capital.

To the best of our knowledge, this is the first study to examine how prior digitalization shapes both AI adoption and AI-related training at the firm level. While directly comparable analyses are lacking, the mechanisms we identify – particularly the role of cumulative digital capabilities and organizational supports – are likely to be relevant beyond the Italian context. Future research could extend this framework to other countries or sectors, testing whether similar path-dependent patterns emerge under different institutional and technological environments

The implications for industrial policy are straightforward: just as active labor market policies often yield better results than passive income support, targeted industrial strategies may prove more effective than fiscal subsidies in building the foundational capabilities needed to support technological upgrading. Public investments in data infrastructures, digital literacy, and firm-university collaborations can strengthen firms' absorptive capacity, enabling broader AI adoption and helping close – rather than widen – existing technological divides.

Managerial implications are equally clear. Firms that invest in internal capabilities and workforce engagement are better positioned to achieve inclusive and sustained digital upgrading. High-road strategies that share gains with workers and other stakeholders can do more than ease adoption – they may enhance returns by fostering commitment and enabling organizational change.

Naturally, some limitations remain. The short observation window restricts our ability to capture long-term effects, and unobserved heterogeneity may still bias our estimates. Moreover, the data do not allow us to distinguish between different types of AI applications or to assess the specific content and intensity of training initiatives. We also lack continuous measures of AI investments and prior digitalization, which would help qualify the intensity of both earlier technological adoption and subsequent AI integration. Finally, our single-country analysis would benefit from comparative cross-country evidence to shed further light on how human-technology dynamics unfold across different institutional settings. Advancing this research agenda will require richer data on the nature of AI applications, training efforts, and their longer-term impacts – critical inputs for both academic research and policy design.

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INAPP

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