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Artificial Intelligence and firm strategies: A pathway to enhanced productivity☆

Syed Muhammad Ali Shah, Marco Cucculelli *

Department of Economics and Social Sciences, Università Politecnica delle Marche, Piazzale Martelli, 8, 60121 Ancona, Italy

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ABSTRACT

This study examines the strategic impact of artificial intelligence (AI) on firm productivity, with a focus on how different strategic goals – customer centricity, international market expansion, and environmental sustainability - interact with AI adoption. We combine professional skills data from LinkedIn with information on innovation activities and strategic objectives collected from company websites for a sample of 1800 manufacturing firms. Using an augmented Cobb–Douglas production function and a two-stage estimation approach, our analysis shows that firms with higher levels of AI intensity tend to exhibit higher production efficiency. However, firms emphasizing customer centricity tend to be less productive, while firms combining higher AI intensity with an international market orientation tend to exhibit higher productivity. By contrast, we find no statistically significant link between AI use and productivity when the strategic goal is environmental sustainability. Overall, the study fills a gap in understanding the role of AI in shaping firm productivity across different strategic orientations, offering valuable insights for optimizing AI intensity and aligning it with strategic planning.

1. Introduction

In recent years, firms across economic sectors have increasingly adopted artificial intelligence (AI), big data, and machine learning technologies to strengthen market positioning and improve operational efficiency. As AI technologies advance rapidly, their implications for firm productivity have become a pressing research concern (Yang, 2022), prompting growing efforts to understand how and why organizations often struggle to align AI adoption with strategic objectives and productivity outcomes (Czarnitzki, Fernández, & Rammer, 2023; Rubio-Andrés, Linuesa-Langreo, Gutiérrez-Broncano, & Sastre-Castillo, 2024; Wilson, Case, & Dobni, 2023).

Existing research suggests that the productivity effects of AI are not automatic. While some firms successfully transform AI-related capabilities into performance improvements, others fail to realize comparable benefits. This indicates that the value of AI depends on organizational capabilities, managerial choices, and the strategic contexts in which it is deployed (Babina, Fedyk, He, & Hodson, 2024; Brynjolfsson, Rock, & Syverson, 2021; Czarnitzki et al., 2023). Prior studies have examined AI in relation to innovation activities (Bahoo, Cucculelli, & Qamar, 2023; Niu, Wen, Wang, & Li, 2023; Wang, Huang, Xia, & Shi, 2024), organizational performance (Babina et al., 2024), employment and inequality (Naudé, 2021; Choi & Leigh, 2024), and scientific discovery (Agrawal, McHale, & Oettl, 2024). Yet, limited evidence exists on whether firms' strategic goals condition the productivity gains associated with AI intensity and AI-related capabilities. This study addresses this gap by examining whether and how strategic objectives shape the relationship

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* Corresponding author.
E-mail addresses: s.shah@pm.univpm.it (S.M.A. Shah), m.cucculelli@univpm.it (M. Cucculelli).

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between AI intensity and firm productivity.

Unlike prior studies, which have primarily focused on the direct productivity effects of AI (e.g., Babina et al., 2024; Czarnitzki et al., 2023) and often treated AI adoption as a homogeneous technological input, this study conceptualizes AI as a strategic capability whose productivity effects depend on its alignment with firms' strategic objectives and organizational resources. By emphasizing this contingent relationship, the study advances the literature on AI and firm performance and helps explain the heterogeneous productivity outcomes associated with AI adoption. This perspective aligns with the emerging view of AI as a strategic capability rather than a stand-alone technological input. As with other general-purpose technologies, the productivity benefits of AI depend on complementary organizational resources, managerial capabilities, and the strategic objectives that guide its deployment and use (Cockburn, Henderson, & Stern, 2018; Raisch & Krakowski, 2021). Consequently, firms with similar levels of AI intensity may realize substantially different productivity outcomes depending on how AI capabilities are embedded within broader strategic priorities.

The notion of boundary conditions is central to understanding these heterogeneous outcomes. While AI enhances firms' ability to process information, generate predictions, and support decision-making, the economic value derived from these capabilities depends on the strategic environment in which they are deployed. Strategic orientations differ in their information-processing requirements, organizational complexity, resource commitments, and reliance on codifiable knowledge. Consequently, the productivity effects of AI may vary across strategic orientations according to the extent to which their objectives can be supported by data-driven analysis and AI-enabled decision-making. This perspective suggests that strategic orientation constitutes an important boundary condition shaping the productivity returns associated with AI adoption.

In the context of firms' strategic actions, recent research has identified three prominent strategic orientations: environmental sustainability (Adomako, Ning, & Adu-Ameyaw, 2021; Danso, Adomako, Amankwah-Amoah, Owusu-Agyei, & Konadu, 2019; Kraus, Rehman, & García, 2020; Singh, Del Giudice, Chiappetta Jabbour, Latan, & Sohal, 2022), international market expansion (Katsikeas, Leonidou, & Zeriti, 2020), and customer centricity (Chen, Zha, Wang, Li, & Bi, 2020; Seok, Kim, & Oh, 2024; Zhao, He, Ma, & Zuo, 2025). These orientations represent distinct pathways through which firms pursue competitive advantage, emphasizing long-term value creation through sustainability initiatives, growth through international expansion, and responsiveness to customer needs. Because they differ in their information requirements, organizational complexity, and resource commitments, they provide an appropriate setting for examining whether the productivity returns associated with AI intensity depend on firms' strategic priorities.

Accordingly, this paper investigates whether the relationship between AI intensity and firm productivity varies according to firms' emphasis on environmental sustainability, international market expansion, and customer centricity. Specifically, it addresses the following research question: To what extent does AI intensity influence firm productivity, and how do these effects differ across firms pursuing distinct strategic orientations?[1]

To empirically examine these questions, we compile a multi-source dataset. Obtaining comprehensive firm-level data across firms remains a challenge when assessing AI intensity and its impact on company performance and decision-making. To address this issue, our study adopts a novel, human-centered methodology that measures AI intensity at firm level through the skill composition of human capital in the organization.[2] Specifically, we extracted data from 600,000 publicly available Italian LinkedIn profiles and collected detailed information on skills, education, and professional experience of employees involved in AI activities in companies. To explore the role of AI, we first classify skills into three categories – AI skills, technical skills (Tech), and soft skills (Soft) - and label profiles as either AI-related or non-AI-related based on their skill sets. Then, each profile receives a score indicating its degree of association with AI, with values closer to one reflecting stronger alignment. Finally, we use this indicator to construct a measure of AI capital at the firm level by aggregating the AI-related knowledge embedded in all employees within each individual company. To complete our dataset, we collect firm-level financial data from the Moody's BvD-Amadeus database, which provides detailed information on the 1800 Italian manufacturing firms included in our sample. To identify the strategic objectives of the sample firms, we gather information from company websites using web scraping and generate variables that summarize the strategic orientation of the company to be used in the analysis of how and to what extent these goals interact with AI intensity in shaping productivity.

Examining these relationships requires a context in which firms face heterogeneous organizational conditions and varying levels of digital transformation, making the strategic contingencies of AI adoption particularly visible. Although our empirical analysis focuses on Italian manufacturing firms, this context is not incidental. Italian manufacturing is characterized by a high prevalence of small and medium-sized enterprises, strong regional heterogeneity, and production systems that combine advanced technologies with relational governance and incremental innovation. These features shape how firms accumulate human skills, organize work, and translate new technologies into productivity outcomes. As a result, Italy provides a relevant setting for examining how artificial intelligence interacts with firm strategies under realistic organizational and institutional constraints, while also allowing us to identify boundary conditions that may differ from large-firm or digitally native contexts.

Our empirical analysis explores how AI intensity interacts with different strategic orientations to influence productivity outcomes, assessing whether AI operates as a complementary or substitutive asset across varying strategic goals. This strategic-contingency perspective moves beyond conventional production function approaches by integrating insights from the resource-based view and dynamic capabilities theory. It allows us to explore how AI complements or conflicts with different strategic orientations – such as customer centricity, internationalization, and environmental sustainability - thereby revealing the heterogeneous mechanisms through

[1] Our focus on customer centricity, international market expansion, and environmental sustainability reflects their importance as distinct strategic orientations in contemporary manufacturing firms. The theoretical rationale for selecting these three dimensions is discussed in Section 2.2.

[2] From our perspective, skill and competency are considered synonymous. Researchers also using the term "competency" (e.g., Sumter, de Koning, Bakker, and Balkenende (2021) use the term "skill" to ensure consistency and enhance understanding.

which AI creates or constrains value.

Our study contributes to the literature on strategy and innovation in several ways. First, we introduce a novel empirical approach that captures AI adoption through human capital skill composition. By combining LinkedIn employee profiles, web-scraped information on firm strategies, and financial records from Amadeus, we construct a unique multi-source dataset that provides a dynamic, capability-based measure of AI intensity and allows us to observe the interaction between AI-related human capital, firm strategy, and productivity outcomes. Second, we extend current research by moving beyond direct AI-performance relationships and examining how different strategic orientations condition the productivity returns from AI adoption. Third, we provide new evidence from the manufacturing sector, illustrating how digital transformation unfolds in a traditional context. While our empirical focus is on Italian manufacturing firms, this setting represents a valuable laboratory for observing AI diffusion among small and medium-sized enterprises. We acknowledge, however, that cultural and institutional factors may limit the generalizability of the findings beyond this context, an issue we discuss further in the limitations section.

The rest of the paper is organized as follows: Section 2 presents the background theory and develops hypotheses. Section 3 describes the data and methods, while Section 4 presents the results. Section 5 concludes. Sections 6 and 7 discuss directions for future research and the study's limitations. The appendix provides additional details on the BERT algorithm, skill classifications, and the construction of AI intensity scores.

2. Theory and hypotheses

2.1. Artificial intelligence: A brief overview

The Organization for Economic Cooperation and Development (OECD, 2024) defines an AI system as *"a machine-based system that, for explicit or implicit objectives, infers from the input it receives how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments."* Economists, however, often adopt varying interpretations. Furman and Seamans (2019) describe AI as *"a loose term used to describe a range of advanced technologies that exhibit human-like intelligence, including machine learning, autonomous robotics and vehicles, computer vision, language processing, virtual agents, and neural networks."* Similarly, Brynjolfsson, Li, and Raymond (2023) define AI as *"an umbrella term that refers to a computer system that is able to sense, reason, or act like a human."* More broadly, Sastry et al. (2024) emphasize AI as *"the study and development of digital systems capable of performing tasks typically associated with human intelligence, often acquired through learning rather than explicit programming."*

Historically, technologies such as the computer and the internet have been recognized as general-purpose technologies (GPTs) because of their wide-ranging technical and economic applications, especially in driving innovation (Lipsey, Carlaw, & Bekar, 2005). AI is now widely considered the latest GPT (Agrawal, Gans, & Goldfarb, 2019a), with profound implications for economic activity. Its economic significance stems from three key features. First, AI enhances prediction capabilities, generating novel business opportunities and fueling product and process innovation through data-driven decision-making. Second, as with other GPTs, AI benefits from the non-rivalrous nature of information goods: while cutting-edge algorithms are often publicly available, firms with access to vast datasets can derive disproportionately greater advantages. Third, as a GPT, AI can be applied broadly to address diverse challenges across many sectors of the economy (Jones & Tonetti, 2020).

2.2. Strategic contingencies of AI adoption

Although artificial intelligence is increasingly recognized as a general-purpose technology, its economic value is unlikely to be uniform across firms. Research grounded in the resource-based view and dynamic capabilities perspective suggests that technologies generate performance advantages only when combined with complementary organizational resources, routines, and strategic objectives (Barney, 1991; Teece, Pisano, & Shuen, 1997). Recent studies similarly emphasize that AI outcomes depend on organizational conditions such as transparency, leadership engagement, governance structures, and strategic integration rather than technology adoption alone (Shahzad, Hoque, Khan, & Arslan, 2026; Tiwari, 2026). From this perspective, AI should be viewed not as a stand-alone productivity-enhancing input, but as a strategic capability whose value depends on how it is deployed within the broader context of the firm.

This perspective has important implications for understanding the relationship between AI and firm performance. While AI can enhance information processing, prediction, and decision-making, the benefits derived from these capabilities depend on the strategic priorities that guide their use. Firms pursuing different objectives often allocate resources differently, develop distinct organizational routines, and face varying operational constraints. Consequently, similar levels of AI intensity may generate different productivity outcomes across firms. Recent work on AI-enabled innovation and business transformation highlights that competitive advantage emerges not from technology adoption itself but from the alignment between AI capabilities and broader strategic goals (Shonubi, 2026). Understanding these contingencies is therefore essential for explaining the heterogeneous performance effects reported in the AI literature.

To examine these strategic contingencies, we focus on three strategic orientations: customer centricity, international market expansion, and environmental sustainability. These orientations were selected because they represent three distinct pathways through which firms pursue competitive advantage in contemporary manufacturing environments. Customer centricity emphasizes market responsiveness and value creation through a deeper understanding of customer needs and increasing product customization (Aftab, Abid, Sarwar, & Veneziani, 2022; Chopra, Bhardwaj, Baber, & Idris Sanusi, 2024; Thangeda, Kumar, & Majhi, 2024). International market expansion reflects firms' efforts to diversify across foreign markets, access new sources of demand, and achieve growth through global competition (Wang, Lu, Huang, & Lee, 2013; Yang, Ye, & Zhu, 2017). Environmental sustainability captures firms' commitment to reducing environmental impacts and adopting cleaner production processes in response to regulatory, market, and societal pressures. Together, these orientations encompass market, growth, and sustainability dimensions that have become increasingly central to contemporary manufacturing strategies. Examining these strategic orientations therefore provides a useful framework for understanding how the productivity effects of AI vary across different organizational contexts.

2.3. AI intensity and firm productivity

Artificial intelligence (AI) is employed to reduce manufacturing costs for existing products and to facilitate the development of a broader range of new offerings, thereby contributing to firm growth (Hottman, Redding, & Weinstein, 2016). The diversity and attractiveness of products depend on a firm's ability to experiment with new and updated knowledge to lower production costs. As a general-purpose technology, AI supports decision-making by leveraging predictive technologies. Firms use big data to evaluate the outcomes of specific experiments, applying algorithms to determine their ultimate impact. This approach not only reduces expenses but also improves efficiency and stimulates innovation in product development (Cockburn et al., 2018).

AI can replace human labor in certain production tasks, resulting in lower labor costs (Agrawal, Gans, & Goldfarb, 2019b). When applied to forecasting a firm's input decisions, AI can effectively reduce forecasting errors. Tanaka, Bloom, David, and Koga (2020) develop a model analyzing companies' input decision-making under various uncertain conditions, finding that forecast errors may lead to either underinvestment or overinvestment. AI, however, can enhance forecasting accuracy by minimizing estimation and prediction errors.

At the same time, several studies caution that productivity gains from AI are not automatic. Implementation costs, data-quality issues, and the need for complementary capabilities can offset potential benefits (Brynjolfsson et al., 2021; Farboodi, Mihet, Philippon, & Veldkamp, 2019). Firms lacking digital infrastructure or skilled personnel may experience limited or even negative short-term effects as resources shift toward AI integration (Bughin, Seong, Manyika, Chui, & Joshi, 2018). Importantly, the ability of firms to translate advanced technologies into productivity gains depends not only on technical adoption but also on human and social capabilities. Evidence from transition and emerging economies shows that social capital, captured through firms' relationships with external stakeholders and institutions, exhibits a non-linear relationship with firm performance and can positively complement innovation activities (Doan, Masciarelli, Prencipe, & Vu, 2023). Similarly, research on small and medium-sized enterprises highlights that human resource management practices play a critical role in enhancing the quality of human capital, supporting innovation, and improving labor productivity (Nam & Luu, 2022). These findings suggest that AI intensity should be understood as a capability embedded within broader human and organizational systems, rather than as a standalone technological input. These conceptual relationships are summarized in Fig. 1.

A substantial body of literature examines firms' use of digital technologies and their effects on productivity. Research by Cette, Devillard, and Spiezia (2021) shows that investment in digital technologies increases labor productivity; similarly, the digitization of small and medium-sized enterprises has been found to contribute positively to firm productivity (Erjavec, Redek, & Kostevc, 2023). However, the magnitude and persistence of these effects remain debated, as several studies show that firms often experience delayed or uneven productivity gains from AI adoption (Brynjolfsson et al., 2021; Filippucci, Gal, Jona Lasinio, Leandro, & Nicoletti, 2024). Based on this mixed evidence, we examine whether AI intensity is associated with productivity improvements in manufacturing firms. To investigate this relationship, we test the following hypothesis:

Hypothesis 1. Firms with greater AI intensity tend to exhibit higher productivity.

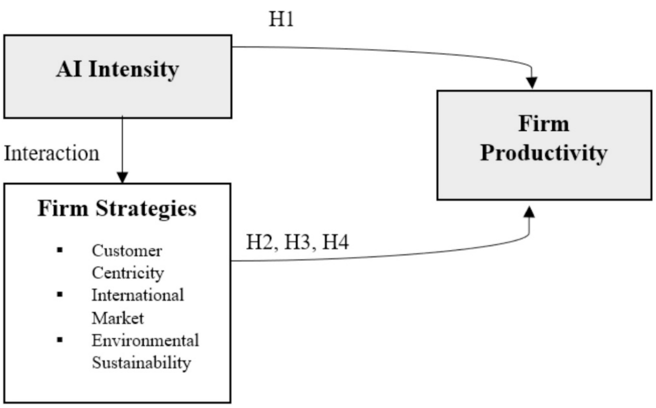

Fig. 1. Conceptual model of AI intensity, strategic orientations, and firm productivity.
Note: The figure illustrates the conceptual framework underlying the study. AI intensity is hypothesized to influence firm productivity directly and conditionally through three strategic orientations: customer centricity, international market expansion, and environmental sustainability. Control variables, industry fixed effects, and regional fixed effects are included in the empirical analysis but are omitted from the figure for simplicity.

2.4. Customer centricity as a strategic contingency

Strategic goals encompass various internal objectives aimed at achieving targets such as high growth through product or process innovation. A primary objective for firms is to develop models that predict customer behavior across different products, as today's consumers are well-informed, sophisticated, and rapidly changing in their demands (Klaus & Zaichkowsky, 2020). Big data, generated and shared by customers online, is essential for firms to forecast customer behavior in the AI era (Kühl, Schemmer, Goutier, & Satzger, 2022). Several studies highlight that AI can anticipate customer needs and preferences, enabling firms to devise more effective strategies (Casabayó, Agell, & Aguado, 2004).

Customer centricity requires complex supply chain management and customizable manufacturing systems, which can increase operational complexity and costs. Pine, Victor, and Boynton (1993) and early research from MIT Sloan Management School have shown that mass customization can provide competitive differentiation. However, it often introduces substantial operational challenges and higher expenses, which may offset the efficiency gains offered by AI-driven insights. These tensions suggest that the relationship between customer centricity, AI intensity, and productivity may not always be positive. High personalization demands can dilute economies of scale, while AI tools may raise coordination and data-management costs (Huang & Rust, 2018). While AI can enhance firms' ability to analyze customer data and anticipate demand, customer-centric strategies also rely heavily on human interaction, coordination, and organizational flexibility. As shown in related literature on human capital and social capabilities, performance gains from innovation-oriented strategies depend on how firms manage these human and relational dimensions (Doan et al., 2023; Nam & Luu, 2022). This implies that combining AI with customer centricity may generate both complementarities and tensions, depending on firms' organizational capacity to absorb complexity.

Despite the growing literature on this topic, the relationship between customer centricity, AI intensity, and firm productivity remains inconclusive. Moreover, no study directly addresses the impact of AI and big data usage on firm productivity.

To investigate this relationship, we test the following hypothesis:

Hypothesis 2. Firms that combine higher AI intensity with strong customer centricity may experience changes in productivity performance.

2.5. International market orientation as a strategic contingency

Firms invest in artificial intelligence (AI) to exert a transformative impact on the global trade sector, reshaping traditional business models and achieving unprecedented levels of productivity (Liu, Chang, Forrest, & Yang, 2020). AI is revolutionizing international trade by enabling firms to better understand market dynamics and participate more effectively in global markets. Organizations leverage algorithms and machine learning techniques to improve analytics, forecast demand, and detect fraud (Raschka, Patterson, & Nolet, 2020). In manufacturing, AI facilitates sentiment analysis, chatbot interactions, and multilingual translation, providing essential tools for cross-border communication. The logistics sector is also undergoing transformation through autonomous vehicles, including self-driving cars and drones, which enhance cost-effectiveness, efficiency, and security in trade (Alzubi, Nayyar, & Kumar, 2018; Devarajan, Go, Lakatos, Robinson, & Thierfelder, 2018). AI tools further optimize delivery routes and improve product distribution efficiency by utilizing real-time data (Oguejiofor et al., 2023; Osman, 2019).

However, concerns remain regarding whether current legal frameworks are adequate to address the unique challenges posed by AI technologies as they reshape the global AI-driven trade landscape (Ehimuan, Chimezie, Akagha, Reis, & Oguejiofor, 2024; Liu et al., 2020). Another critical issue in this context is product liability, particularly concerning the safety and reliability of AI systems and products. Questions regarding the potential liability of manufacturers, distributors, and sellers for defects or malfunctions are increasingly relevant as AI technologies are integrated into consumer products, industrial machinery, autonomous vehicles, and other goods and services (Buiten, 2024). In addition, the benefits of AI for international expansion may be uneven. Smaller firms may lack the scale to capitalize on data-intensive insights, and market entry risks can offset productivity improvements (Bäck, Hajikhani, Jäger, Schubert, & Suominen, 2022; Benabed, Miksik, Baldissera, & Gruenbichler, 2022). Regulatory and cultural differences may also limit the effective transfer of AI-based practices across borders.

Despite these developments, the effects of international market strategies and firms' AI intensity on productivity remain insufficiently understood. To investigate this relationship, we formulated the following hypothesis:

Hypothesis 3. Firms combining higher AI intensity with strong international market orientation tend to exhibit greater productivity.

2.6. Environmental sustainability as a strategic contingency

Businesses are increasingly recognizing the importance of environmental sustainability due to the widespread impact of climate change across the globe. Sustainability is a multidimensional concept encompassing environmental, social, and economic aspects. The coexistence of thriving economies with environmental degradation is unsustainable, as pursuing environmental sustainability entails inherent risks that can affect corporate operations and competitiveness in the market (Patel, Pearce II, & Oghazi, 2021). Companies worldwide are therefore encouraged to use resources efficiently to minimize carbon emissions and protect the environment (Calise et al., 2019). Various sectors across many countries are experiencing adverse environmental impacts, which not only pose significant challenges but also contribute to economic crises (Abdella et al., 2021). Moreover, Van Wynsberghe (2021) argues that increased utilization of artificial intelligence (AI) could potentially lead to additional environmental risks.

Nevertheless, some studies suggest that firms with explicit environmental sustainability objectives tend to demonstrate higher levels of innovation and are better able to rapidly identify and respond to market and customer demands (Bos-Brouwers, 2010; Rauter, Globocnik, Perl-Vorbach, & Baumgartner, 2019). These firms also prioritize the production of eco-efficient products (Demirel & Kesidou, 2019). Also, firms committed to environmental protection often allocate additional resources to capture new markets through AI technologies, which can increase production costs due to the need for efficient resource utilization. Moreover, sustainability-oriented strategies may be shaped by ethical and institutional constraints rather than productivity-enhancing motives alone. Evidence from dynamic business environments shows that firms often adopt formal or compliance-oriented practices in response to regulatory pressure and governance conditions, which may increase costs without improving efficiency (Vu, Nguyen, Hoang, & Cuong, 2024). In such settings, sustainability efforts may be decoupled from operational optimization, suggesting that the interaction between AI intensity and environmental sustainability may not yield immediate productivity gains.

Overall, this discussion highlights the critical importance of environmental sustainability for both firms and global economies. However, the impact of AI on the productivity of firms pursuing environmental sustainability strategies remains unclear, as integrating AI into sustainability strategies can create trade-offs: while AI may support resource optimization and emission reduction, its development and computational intensity can increase energy consumption (Strubell, Ganesh, & McCallum, 2019). Consequently, the net productivity effect of AI under a sustainability focus is theoretically ambiguous.

To investigate this relationship, we formulated the following hypothesis:

Hypothesis 4. The interaction between AI intensity and environmental sustainability orientation influences firm productivity.

3. Data and methods

The use of social media data has gained significant popularity across various research domains, including economic analysis, due to its wide range of potential applications. A growing number of researchers are investigating firm behavior (Bottai, Crosato, Domenech, Guerzoni, & Liberati, 2024; Rizov, Vecchi, & Domenech, 2022), employee capabilities, and labor market dynamics by leveraging data derived from social media platforms (Berry, Maloney, & Neumark, 2024; Gajdzik & Wolniak, 2022). In particular, scholars are interested in exploring the unique insights that can be extracted from social media data - insights that are often unavailable from traditional sources. For example, Schneider and Harknett (2019) use Facebook Ads data to examine work schedules across several companies. Similarly, economists have employed social media data, such as job postings, job applications, and Facebook Ads, to study company behavior, minimum wages, and employee skills (Azar, Marinescu, & Steinbaum, 2022; Borup & Schütte, 2022; Clemens, 2021; Marinescu & Wolthoff, 2020; Neumark, Burn, & Button, 2019).

Our primary data source consists of publicly available detailed profiles of individuals residing in Italy and listed on LinkedIn. LinkedIn is regarded as a particularly valuable platform for human capital information: job seekers create profiles that include comprehensive details on their expertise, skills, and professional background, while firms use the platform primarily for recruitment and talent evaluation. For this study, we extracted approximately 600,000 publicly accessible Italian profiles from LinkedIn.[3] The data collection was conducted through web scraping of publicly available profiles using authorized APIs provided by third-party companies, all of which comply with LinkedIn's terms and restrictions.

These LinkedIn profiles contain information on individuals' educational background, year of graduation, degree and institution attended, work experience, job history, current job description, employer details, and – most importantly - their skill sets. While previous studies have relied on job-vacancy data to measure human capital and inform economic analysis, our approach focuses instead on employee profiles. Job posting data related to AI has notable limitations: it reflects only the demand for specific skills, without capturing whether the positions are filled or what happens afterward. As such, relying solely on vacancy data risks overestimating AI intensity. Moreover, job postings do not account for existing employees who acquire advanced technologies and skills through industry training, workplace experience, or peer learning, and who are already engaged in AI-related tasks. By contrast, employee profiles provide more precise and dynamic information about individuals within the same firm across different job positions over time. This profile-based approach yields more reliable results and mitigates the risk of over- or underestimating AI intensity in companies.

Exhibit 1 summarizes the main information captured by each data source and highlights their contribution to the empirical design. The integration of LinkedIn employee profiles, website-derived strategic information, and Amadeus financial records allows us to connect AI-related human capital, firm strategies, and productivity outcomes within a single analytical framework. This multi-source approach represents a key contribution of the study, as it provides a dynamic and capability-based measure of AI intensity while enabling a direct examination of how strategic orientations condition the productivity returns associated with AI adoption.

To our knowledge, previous studies typically combine firm financial information with either patent data, innovation indicators, or job-vacancy records. By contrast, our approach integrates employee-level AI skills, website-derived strategic information, and firm-level financial outcomes within a single analytical framework. This enables us to simultaneously observe AI-related capabilities, strategic orientations, and productivity performance, thereby providing a unique opportunity to examine how the productivity returns associated with AI intensity vary across different strategic contexts.

[3] LinkedIn data provide extensive information on employee skills, they may overrepresent individuals who are more digitally active or employed in technology-oriented roles. To mitigate potential selection bias, we compared the distribution of firms in our dataset with official ISTAT (2023) manufacturing statistics and found close alignment in firm size, industry composition, and regional coverage. This consistency supports the representativeness of our sample, although we acknowledge that LinkedIn data may not capture all employees equally across firms.

Exhibit 1
Contribution of the multi-source dataset.

Data Source	Information Captured	Contribution
LinkedIn employee profiles	AI-related skills and human capital characteristics	Dynamic measure of AI intensity
Corporate Websites	Strategic objectives and innovation activities	Identification of strategic orientation and innovation behavior
Moody's BvD-Amadeus	Productivity and financial indicators	Measurement of firm performance outcomes
Combined Dataset	AI capabilities, strategic orientations, and performance outcomes (productivity)	Enables examination of strategic contingencies in the AI-productivity relationship.

Note: The exhibit summarizes the complementary information obtained from each data source and shows how the integration of employee-level skills, website-derived strategic information, and financial records enables the empirical analysis of AI intensity, strategic orientations, and firm productivity.

3.1. Sample description

We build our dataset from three different data sources: (i) detailed employ-level data from LinkedIn, used to construct the proxy for AI intensity at company level, (ii) innovation and strategic goal data from companies' websites, and (iii) company financial data from Moody's BvD-Amadeus. Sample data include approximately 1800 manufacturing companies operating in Italy. For the empirical analysis, we constructed a treatment group that includes 600 manufacturing firms identified as AI users based on employee skill profiles collected from LinkedIn. For each AI-using firm, approximately two non-AI firms were matched from the same two-digit ATECO industry, region, and firm-size category, resulting in a control group of about 1200 firms. This matching procedure helps ensure that any observed productivity differences are less likely to be driven by sectoral, regional, or size differences. We also verified that the overall distribution of firms by size and industry aligns with national manufacturing statistics from ISTAT (2023), confirming that the sample is broadly representative of the Italian manufacturing sector. Table A1 in the Appendix shows the regional and firm-size distribution of the sample and the corresponding average AI intensity, indicating broad coverage across Italian regions and size classes. Table A2 presents the distribution of firms across ATECO manufacturing sectors (codes 10–33), distinguishing between AI-using and non-AI firms. The composition closely mirrors the national structure of Italian manufacturing, showing that the sample is not concentrated in a few specific industries.

The data regarding the strategic goals and innovation activities of firms is extracted using a text mining method from the websites of these companies, while the financial indicators of companies are extracted from Moody's BvD-Amadeus. This procedure ensures that we examine profiles with a full set of relevant information available, thereby ensuring reliability in the results of our research.

3.2. Employee profile scoring

Profile scoring enables the allocation of precise AI intensity scores to individual profiles based on the skills possessed by employees found in LinkedIn. For each profile, we calculate the overall count of distinct skills, their distribution in terms of frequency, and the associated language. We perform lowercasing to ensure that identical skills are not considered distinct due to differences in case. We employ the Bidirectional Encoder Representations from Transformers (BERT) model for this specific objective. We trained our machine learning BERT model using a dataset consisting of the top two hundred skills in the fields of AI, Tech, and Soft skills.[4] This model possesses the advantageous capability of effectively managing synonyms and variations, as well as analyzing out-of-vocabulary words. It also demonstrates proficiency in transfer learning and excels in handling multi-class classification of skills. To enhance transparency, we report the main training and validation details in the text. The model was fine-tuned on a manually labeled dataset of 200 skill terms, divided into 80% for training and 20% for testing. Validation results show high performance (F1-score 0.92, precision 0.90, recall 0.94), confirming the model's reliability in classifying employee skills (further implementation details are provided in the appendix). To enable dynamic scoring of skills, we assign values of 0, 1, and 2 to the AI, Tech, and Soft skills, respectively. We calculate the frequency distribution of each skill in the entire dataset of data skills and determine the weightage of each skill.

$$Weightage\ of\ each\ skill = \frac{Frequency\ of\ Skill\ in\ database}{Sum\ of\ frequencies\ of\ all\ skills} \tag{1}$$

Our method of using skills as a proxy for AI intensity in firms represents an alternative to measures used in different strands of the literature. Babina et al. (2024) use skills data from Cognism and job posting data; Alderucci and Ashley (2020) and Webb (2019) take advantage of patent descriptions, and Abis and Veldkamp (2024) use skills for advanced and old technologies. These alternative methodologies rely on matching the occupational structure of companies with advancements in AI technologies. The scoring techniques demonstrate the combination of condition-based multipliers, recognizing the diverse spectrum of AI abilities and their distinct impact on the overall degree of AI-intensity in a profile.[5] To compute the AI intensity at firm level, we followed the following procedure: if the fraction of AI skills in the individual profile exceeds 30%, the AI-multiplier, tech-multiplier, and soft-multiplier are

[4] Check Appendix Table A4 for AI skills, A5 for Tech skills, and A6 for Soft skills.
[5] AI intensity scores capture the degree of association between an employee profile and AI-related activities, providing a more refined measure than a simple binary classification indicating the presence or absence of AI-related skills.

assigned values of 0.6, 0.025, and 0.015, respectively. Conversely, if the AI skill frequency distribution is less than 30%, the AI-multiplier is assigned a value of 0.5, while the tech-multiplier and soft-multiplier are assigned values of 0.035 and 0.015, respectively[6] (for AI intensity scores see appendix, Table A7).

The key factor in determining the scoring of our profile in this approach is the complexities of skill categorization, dynamic multipliers, and weightages. Therefore, the overall score is determined by the combined contribution of three unique categories: AI skills, tech skills, and soft skills. This comprehensive measure accurately encompasses the extent and intensity of an individual's AI-related skills. Normalization is an essential process that ensures fair and unbiased comparison across different profiles. By computing the highest and lowest scores across all profiles, we incorporate a measure of magnitude into our scoring system. The normalized scores offer a standardized metric that indicates the relative degree of connection with AI for each profile in the sample. Essentially, our profile scoring technique goes beyond a mere numerical exercise. It involves thoroughly examining skills, engaging with the intricacies of AI-related knowledge, and systematically collecting important insights from the vast amount of data. This scoring procedure allows us to capture both the breadth and intensity of AI-related skills within each profile and to aggregate this information at the firm level. We extracted all the manufacturing companies from our dataset, specifically focusing on the manufacturing sector. We focus on manufacturing firms because they provide a suitable setting for examining how AI intensity interacts with strategic goals in production-oriented activities.

Fig. 2 shows the AI intensity in the Italian provinces, with dark blue indicating higher AI intensity in these provinces compared to others.

We perform this procedure on data from the past ten years, specifically from 2014 to 2023. We combine all the employees and generate an AI intensity for each firm. The AI intensity for each firm is determined annually based on the employees' joining information, job descriptions, and skill sets. Therefore, the AI intensity is a time-varying variable that provides dynamic information on the evolving AI profile of each company in the sample. We aggregate the annual scores of AI-related firms by summing the total number of employees within the same year and across the same companies. To analyze the AI intensity within these firms, we calculate the ratio of AI-related employees to total employees in these firms over the past decade.

The line graph in Fig. 3 represents the progressive change in the proportion of labor contributed by artificial intelligence (AI) within companies from 2014 to 2023. The computation of the AI labor share involves aggregating the AI-related recruitment scores for each firm annually. These scores are then standardized based on the total number of employees and aggregated across all firms. This indicator provides a quantifiable measurement of the level of AI-related skills and capabilities among the workforces. Remarkably, there has been a noticeable rise in the proportion of labor related to artificial intelligence (AI), indicating substantial growth in the integration of AI knowledge and skills within organizations over time. To assess this progress, we compute the yearly percentage increase in the ratio of AI labor compared to the baseline year, 2014. The results emphasize a significant trend, marked by a steady rise in the AI intensity in the period. This notable growth demonstrates the substantial and continuously growing impact of AI-related skills in shaping the present workforce landscape. Moreover, this graph depicts the number of employees working in AI-related professions across manufacturing firms in Italy over the past decade. The consistent growth in the accumulation of AI human capital from 2014 to 2023 suggests that it has increased ninefold over the past decade.

Although the econometric analysis is conducted at the firm level, the AI-intensity indicator itself is dynamic in construction. Specifically, AI intensity is derived from yearly observations of employee skills and occupational profiles covering the period 2014–2023. The measure therefore captures the accumulation and evolution of AI-related human capital within firms over time rather than a static indicator of technology adoption. The empirical analysis utilizes the most recent firm-level realization of this accumulated capability stock, allowing us to examine how long-term AI capability development is associated with productivity differences across firms.

3.3. *Identification of strategic goals*

Determining the innovativeness and the strategic approach of firms is a complex task due to the unique and often hidden nature of innovation and strategy, which are very difficult to quantify using data. Recently, there has been an upward trend in using text mining and text analytics to extract valuable information from company websites (Rammer & Es-Sadki, 2023). This approach aims to identify the unique characteristics of companies and uncover insights about their products, services, target audience, and overall objectives and strategies. Such information is then utilized for economic analysis purposes (Gentzkow, Kelly, & Taddy, 2019). The use of text mining techniques and the accessibility of this type of data provide valuable avenues for research to identify firms' strategic objectives and assess their innovation activities, among other things.

Kinne and Lenz (2021) employ text mining data to identify the innovation endeavors of companies based on their websites. The text data is extracted using automated technologies, and topic modeling is employed to analyze the subjects using neural network methods. This allows for the identification of companies' initiatives to innovate. Kinne and Lenz (2021) use an artificial neural network model to

[6] The 30% threshold used to assign the AI multiplier was determined to reflect cases where AI-related skills constitute a substantive share of an employee's overall skill set. This ensures that profiles heavily oriented toward AI activities contribute proportionally more to a firm's AI-intensity measure. The specific value (0.6) serves as a comparative weight emphasizing AI expertise relative to technical and soft skills; alternative scaling values (e.g., 0.7 or 0.8) would yield equivalent fractional relationships. This threshold-based weighting approach is consistent with previous studies that operationalize AI specialization through proportional measures of AI-related skills within occupational profiles (Abis & Veldkamp, 2024; Webb, 2019). Robustness tests using 20 and 40% cutoffs produced similar results, confirming that our findings are not sensitive to the chosen threshold.

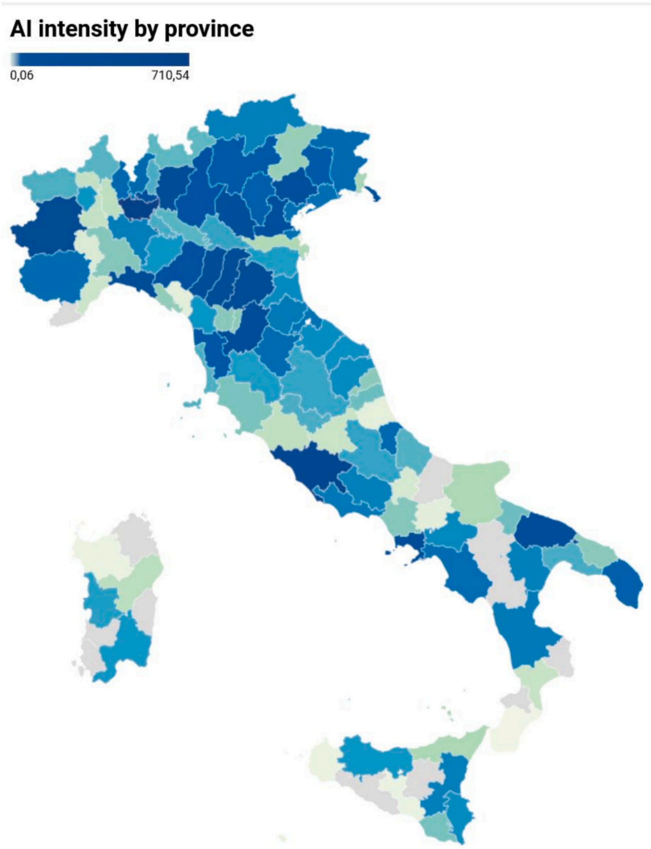

Fig. 2. AI intensity by province - Italy.
Note: The map reports the geographical distribution of AI intensity across Italian provinces. AI intensity is measured as the ratio of AI-related employee skills to total employee skills within firms and aggregated at the provincial level. Darker shades indicate higher levels of AI intensity. The figure highlights substantial regional heterogeneity in the diffusion of AI-related capabilities across Italian manufacturing firms.

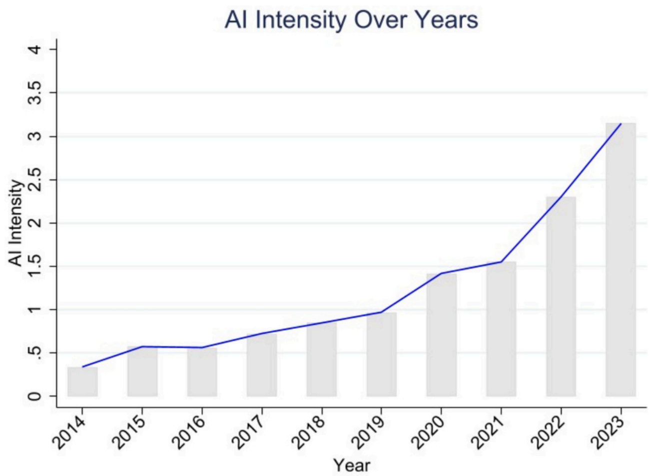

Fig. 3. Evolution of AI intensity, 2014–2023.
Note: The figure shows the evolution of AI intensity among manufacturing firms over the period 2014–2023. AI intensity is computed annually using employee-level skill information extracted from LinkedIn profiles. The upward trend indicates a substantial increase in AI-related human capital and capabilities within Italian manufacturing firms over time.

analyze the web text of several German companies. They utilize a pre-trained web text model to identify the innovative activities of these firms and subsequently compare the outcomes with traditional indicators. They determine that this method offers a novel signal for the innovation activities of companies based on textual data.

Following Kinne and Lenz (2021), we use a pre-defined set of keywords related to product and process innovation (Marzi, 2022; Marzi, Dabić, Daim, & Garces, 2017), customer centricity (Urbany & Dapena-Baron, 2025), international market expansion (Rundh, 2023), and environmental sustainability (de Oliveira Neto et al., 2020; Ioannou & Serafeim, 2019). We use these keywords to find companies' strategies from their websites to determine if they have objectives and strategies related to product innovation, process innovation, customer centricity, international market expansion, and environmental sustainability. We gather data regarding the innovative activities of the firms along with their strategies and objectives, including specific targets and detailed descriptions. Specifically, we identify three strategic goals pursued by these firms: environmental sustainability, customer centricity, and international market expansion. We also determine whether these companies are engaged in product innovation, process innovation, or both. As companies use different terminology to describe product innovation, process innovation, environmental sustainability, customer centricity, and international growth on their websites, we used a wide set of keywords (Table 1) to determine whether these companies are engaged in innovation activities and whether they are also pursuing these three strategic goals.[7]

Table 2 shows the distribution of the three strategic goals across our full sample manufacturing firms. Customer centricity and international market orientation are widely represented, while environmental sustainability is less frequent. Specifically, around 84% of firms reference customer-centric strategic priorities on their websites, and nearly 69% highlight some form of international engagement. In contrast, only 40% explicitly mention environmental sustainability objectives. These descriptive patterns help clarify the strategic landscape in which firms operate and provide important context for interpreting the later interaction effects with AI intensity.

3.4. Definition of the variables

Our dependent variable is firm productivity, measured by the ratio of value added to total employees. This ratio reflects the production efficiency measured using labor productivity at firm level.

We use employee skill-level data from the sample firms to determine each company's AI stock and to quantify its AI intensity. A firm's AI stock is calculated as the total number of AI-related skills possessed by its employees. This value is then divided by the total number of employees to obtain the firm's AI intensity. AI intensity, product innovation, environmental sustainability, customer centricity, and international market expansion constitute the main variables in our model. AI intensity is a continuous variable capturing the extent of AI adoption within the firm. Product innovation is a binary variable indicating whether the firm engages in product-level innovative activities. Environmental sustainability, customer centricity, and international market expansion are binary variables reflecting the firm's strategic priorities. All variables related to innovation and strategic objectives were extracted from company websites using sets of predefined keywords.

To control for potential confounding factors and avoid the omitted variables problem, several controls have been included in the model: firm size (total number of employees), firm age (years since birth); firm capital (to account for investments in production capacity), leverage (percentage of debt in the capital structure). We include a binary variable for non-independent firms to account for different organizational structures. Also, a dummy for foreign-owned enterprises has been included, together with the Herfindahl-Hirschman Index (HHI)[8] to measure market concentration and competitive environment. Industry-specific (4-digits NACE ATECO codes) fixed effects control for varying levels of capital intensity, technology adoption, and competitive pressures across industries; the model also includes regional fixed effects. The final estimation sample varies slightly across specifications because some financial and strategic variables are unavailable for all firms. Consequently, observations with missing values are excluded from the relevant regressions.

Table 3 indicates substantial variation in AI intensity, firm productivity, and strategic orientations across the sample. This variation provides the empirical basis for examining whether the productivity effects of AI differ according to firms' strategic priorities. Before turning to the multivariate analysis, Table 4 reports the pairwise correlations among the main variables.

Table 5 compares the prevalence of each strategic orientation between AI-using firms and non-AI firms. The descriptive evidence indicates that AI adopters and non-adopters differ significantly in their strategic profiles. AI-using firms are somewhat less likely to emphasize customer centricity or sustainability, and more likely to report international market orientation relative to non-AI firms. These differences support the idea that AI adoption is embedded within broader strategic choices, underscoring the relevance of examining AI–strategy complementarities in the main empirical analysis.

[7] To check the reliability of our web-scraped data, we manually reviewed a random sample of 180 firm websites, i.e. approximately 10% of the sample population. Two researchers independently verified whether the automated keyword classification aligned with the firms' stated strategic goals. The review showed a high level of accuracy (precision 88%, recall 83%, Cohen's $\kappa = 0.82$), suggesting strong consistency between the automated and manual classifications. Since 40–85% of the firms in our sample report these strategic orientations, the results indicate that any potential classification errors are limited and unlikely to affect the overall findings. This validation approach is in line with the recommendations of Rammer and Es-Sadki (2023), who highlight firm websites as a credible and replicable data source for studying innovation and strategic behavior.

[8] We compute the Herfindahl-Hirschman Index (HHI) for three-digit NACE ATECO codes. We compile the market share of each firm by dividing the firm's revenue by the total revenue of all the firms in these NACE ATECO codes, which is approximately 350,000 firms.

Table 1
Keywords for strategic goals and innovation activities.

No.	Product Innovation	Environmental Sustainability	Customer Centricity	International Market
1	New Product Development	Sustainable Practices	Customer-focused Approach	Global Expansion
2	Innovative Products	Eco-friendly Initiatives	Customer Satisfaction	International Market Penetration
3	Product Design and Development	Green Technology	Customer Experience Enhancement	Market Diversification
4	Cutting-edge Solution	Environmental Stewardship	Personalized Services	Global Market Presence
5	R&D Initiatives	Carbon Footprint Reduction	Customer Engagement	Cross-border Operations
6	Novel Offerings	Renewable Energy Adoption	Client-Centric Solution	Foreign Market Entry
7	Product Differentiation	Waste Reduction Strategies	Voice of Customer	International Sales Growth
8	Breakthrough Products	Conservation Efforts	Customer Loyalty Program	Expansion into new territories
9	Advanced Technology Products	Climate Change Mitigation	Responsive Customer Service	Market Globalization

Note: The table presents illustrative examples of keywords used to identify firms' strategic orientations and innovation activities from website text. The full keyword dictionary includes additional synonyms and related expressions. Firms are classified as pursuing a given strategic goal when at least one keyword from the corresponding dictionary is identified within website content.

Table 2
Distribution of strategic priorities among firms

Strategic Goal	Value	Frequency	Percent	Cumulative	Firms with values = 1
Customer Centricity	0	278	15.58	15.58	84.42
	1	1506	84.42	100.00	
International Market	0	558	31.28	31.28	68.72
	1	1226	68.72	100.00	
Environmental Sustainability	0	1079	60.48	60.48	39.52
	1	705	39.52	100.00	

Note: Values represent the number and percentage of firms that explicitly reference each strategic goal on their websites. A value of 1 indicates that the firm reports the corresponding strategic goal, while 0 indicates that it does not. Percentages reflect the share of firms within the total sample. These descriptive statistics provide an overview of the distribution of strategic orientations and inform the interpretation of later interaction effects between AI intensity and strategic orientations.

3.5. Baseline empirical model

We employ the extended form of the Cobb-Douglas production function model to evaluate our theoretical hypotheses. This model estimates the relationship between AI intensity at firm level, its innovation activities, and productivity. The Cobb-Douglas production function for firm productivity typically takes the following form:

$$Y = A.L^{\alpha}.K^{\beta} \tag{2}$$

We employ the approach of Czarnitzki et al. (2023) to estimate the augmented Cobb-Douglas production function using AI intensity as an input.

$$\mathrm{Y_i = A_i.L^{\alpha}{}_i.K^{\beta}{}_i.AI^{\partial}{}_i} \tag{3}$$

We determine the efficiency of firm *i* dividing the value added, denoted as Y_i, by the total number of employees. $L^{\alpha}{}_i$ is the labor input, which represents the number of workers employed at a particular firm. $K^{\beta}{}_i$is the capital stock of the firm, while $AI^{\partial}{}_i$ is the AI intensity at firm level. Parameters α, β, and ∂ are unknown and must be estimated.

3.6. The regression model

To test Hypothesis 1, we use two-stage estimation approach that also allows us to address potential endogeneity and reverse causality between AI intensity and firm productivity. In the first stage, we regress AI intensity on control variables:

$$AI\ Intensity_i = \beta_0 + \sum_k \beta_k^{(c)}\ Controls_{ik} + u_{1i} \tag{4}$$

Where k = index for each control variable (so k = 1,2, 3, …); $\beta_k^{(c)}$ = the coefficient on the k-th control variable and $Controls_{ik}$ = the value of the k-th control variable for firm i. The superscript (c) just reminds that these are the control-variable coefficients, not the main ones of interest. After estimating the predicted value of AI intensity utilizing Eq. 4, we use the predicted values in the production function in eqs. 5 and 6 (second stage), respectively. The difference between the two equations lies in the fact that Eq. 6 includes the interaction terms between AI intensity and the firms' strategies.

Table 3
Definition and summary statistics.

All Firms (observations: 1800)
AI and Non-AI Users

Variable	Definition	Mean	Std. dev	Min	Max
AI Intensity	AI intensity is the weighted sum of AI-related skills of employees in the company.	0.007	0.098	0	3.818
Efficiency (log)	The ratio of firm's value added to the total number of employees (log value).	11.22	0.631	6.985	13.04
Revenue (log)	The ratio of the total revenue to the total number of employees (log value).	5.468	0.867	−0.336	9.629
Capital (log)	The ratio of the total stock of capital to the total number of employees (log value).	1.537	0.732		12.77
Leverage	The ratio of firm financial debt on total assets.	3.993	36.41	−1257.4	452.42
HHI	The Herfindahl-Hirschman Index is to measure market concentration for industries at the ATECO 3-digit level.	209.89	558.93	8.779	7842.6
R&D Expenditure	The ratio of firm spending on research and development activities to the total number of employees.	−2.379	2.974	−9.374	7.109
Corporate Firm	A binary variable that takes the value of one if a company is classified as a corporate entity, and zero otherwise.	0.382	0.486	0	1
Foreign Firm	A binary variable that takes the value of one if a company is classified as a foreign firm, and zero otherwise.	0.355	0.479	0	1
Customer Centricity	A binary variable that takes the value of one if a company expresses a customer centricity concern and mentions one of the keywords associated with customer centricity, and zero otherwise.	0.844	0.363	0	1
International Market	A binary variable that takes the value of one if a company expresses an international market concern and mentions one of the keywords associated with international market, and zero otherwise.	0.687	0.464	0	1
Environmental Sustainability	A binary variable that takes the value of one if a company expresses an environmental sustainability concern and mentions one of the keywords associated with environmental sustainability, and zero otherwise.	0.395	0.489	0	1
Product Innovation	A value of one is given to a binary variable if the company has mentioned one of the product innovation keywords on their website, and zero otherwise.	0.837	0.369	0	1
Firm size (log)	Number of employees in a firm (log value).	4.221	1.809	0	10.53
Firm age (years)	The number of years since the firm birth.	28.99	18.86	0	145

AI Users (observations: 600)

Variable	Definition	Mean	Std.dev	Min	Max
AI Intensity		0.021	0.173	0	3.818
Efficiency (log)		11.40	0.565	6.984	13.04
Revenue (log)		5.680	0.864	−0.336	9.629
Capital (log)		1.564	0.776	0	12.78
Leverage		1.558	54.52	−1257.4	83.79
HHI		216.92	575.39	8.779	7842.6
R&D Expenditure		−2.433	3.278	−9.374	5.520
Corporate Firm		0.465	0.499	0	1
Foreign Firm		0.305	0.461	0	1
Customer Centricity		0.775	0.418	0	1
International Market		0.613	0.488	0	1
Environmental Sustainability		0.350	0.477	0	1
Product Innovation		0.829	0.377	0	1
Firm size (log)		4.779	1.806	0	10.54
Firm age (years)		29.45	18.72	1.3	126

Non-AI Users (observations: 1200)

Variable	Definition	Mean	Std.dev	Min	Max
AI Intensity		0	0	0	0
Efficiency (log)		11.13	0.641	7.021	12.93
Revenue (log)		5.369	0.851	1.609	8.686
Capital (log)		1.523	0.710	0	6.919
Leverage		5.175	22.89	−411.5	452.4
HHI		206.4	550.8	8.779	7842.6
R&D Expenditure		−2.352	2.812	−7.883	7.109
Corporate Firm		0.340	0.474	0	1
Foreign Firm		0.381	0.486	0	1
Customer Centricity		0.878	0.327	0	1
International Market		0.724	0.447	0	1

(*continued on next page*)

Table 3 (*continued*)

Non-AI Users (observations: 1200)					
Variable	Definition	Mean	Std.dev	Min	Max
Environmental Sustainability		0.417	0.493	0	1
Product Innovation		0.841	0.366	0	1
Firm size (log)		3.962	1.752	0	8.711
Firm age (years)		28.77	18.94	0	145

Note: This table reports variable definitions and descriptive statistics for the full sample, AI-using firms, and non-AI firms. AI intensity is measured as the weighted ratio of AI-related employee skills to total employee skills within a firm. Binary strategic-orientation variables take the value of one when the corresponding objective is identified through website text analysis and zero otherwise.

$$
\begin{aligned}
Y_i(Productivity) = {} & \beta_0 + \beta_1 \boldsymbol{Predicted\ AI\ Intensity}_i + \beta_2 \log(Capital_i) \\
& + \beta_3(Employment_i) + \sum_k \beta_k^{(c)}\ other\ Controls_{ik} \\
& + \delta Industry\ FE_{ji} + \gamma Region\ FE_{ri} + \varepsilon_i
\end{aligned} \tag{5}
$$

The choice to employ a two-stage estimation approach follows the well-established CDM framework (Crépon, Duguet, & Mairessec, 1998; Griffith, Huergo, Mairesse, & Peters, 2006), which is widely used when external instruments are not available. Reverse causality is a potential concern in cross-sectional firm-level studies, as more productive firms may also be more likely to adopt AI technologies. Our two-stage approach helps to mitigate this issue by first modeling the determinants of AI intensity and then using the predicted values in the productivity equation. This separation reduces simultaneity bias and measurement error in the AI-intensity variable, allowing for a more credible assessment of its effect on firm productivity. While this procedure alleviates endogeneity concerns, we acknowledge that some residual bias may persist in the absence of panel data or strong external instruments. Moreover, we check multicollinearity using variance inflation factors (VIFs). Table 4 shows that all VIF values fall below standard thresholds, suggesting that multicollinearity does not compromise model stability.

In Eq. 6, we include the interaction term between predicted AI intensity and firm strategies to examine whether the association between AI intensity and productivity varies across different firm strategies. To test Hypotheses 2, 3, and 4, we employ the following model.

$$
\begin{aligned}
Y_i(Productivity) = {} & \beta_0 + \beta_1 \boldsymbol{Predicted\ AI\ Intensity}_i + \beta_2 \log(Capital_i) + \beta_3(Employment_i) + \beta_4(\boldsymbol{Predicted\ AI\ Intensity}_i \\
& \times \boldsymbol{Strategic\ Goal}_i) + \beta_5(\boldsymbol{Strategic\ Goal}_i) + \sum_k \beta_k^{(c)}\ other\ Controls_{ik} \\
& + \delta Industry\ FE_{ji} + \gamma Region\ FE_{ri} + \varepsilon_i
\end{aligned} \tag{6}
$$

4. Results

4.1. AI intensity and firm productivity

In the first stage (Appendix, Table A3), we regress AI intensity on firm characteristics. Results show that younger and smaller firms, and those with greater capital intensity, are associated with higher levels of AI intensity. R&D expenditure does not appear to be a significant driver. Industry and regional fixed effects explain a large share of the variation, suggesting that sectoral and locational factors are important determinants of AI use.[9] The predicted values of AI intensity obtained from these estimates are used in the second stage of the model, i.e., the productivity equations (Tables 6–9). Table 6 shows the results of AI intensity and firm productivity in column (1) to (4). In this second stage, we control for industry (4-digits NACE ATECO codes) fixed effects and regional fixed effects.

The results reported in columns (1) and (2) show the relationship between (observed) AI intensity and firm productivity, when AI intensity is used as the explanatory variable. To control for additional factors influencing productivity dynamics at the firm level, we include lagged revenue per employee (2021) as a proxy for differences in demand conditions and market position. This approach follows the tradition of the CDM model (Crépon et al., 1998), where lagged sales are commonly used as a proxy for firm size and absorptive capacity (Griffith et al., 2006). The positive and significant coefficients associated with firm size, measured by the total number of employees, further highlight its importance for productivity. However, the squared employment term reveals an inverted U-shaped relationship, suggesting that efficiency rises with firm size up to a certain threshold, after which it begins to decline.

While the OLS estimates in columns (1) and (2) provide preliminary evidence that AI intensity is positively associated with productivity, issues such as endogeneity, measurement error, and reverse causality may bias these results. To address these concerns, we

[9] The first-stage results (Table A3) indicate that firm size, capital intensity, age, and industry/regional conditions are strong predictors of AI intensity, with the model's explanatory power rising from 0.037 to 0.602 once fixed effects are included. These variables therefore play an important role in reducing simultaneity between AI adoption and productivity. However, we acknowledge that they do not serve as perfect exclusion restrictions, and thus our two-stage approach should be viewed as reducing - rather than eliminating - potential endogeneity. For this reason, we supplement the main analysis with a TFP-based robustness check, which confirms the stability of all key results.

Table 4
Correlation matrix.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	VIF	1/VIF
(1) AI Intensity	1.00															1.05	0.95
(2) Efficiency (log)	−0.09	1.00														1.75	0.57
(3) Revenue (log)	−0.08	0.74	1.00													1.45	0.69
(4) Capital (log)	0.11	0.06	0.12	1.00												1.63	0.61
(5) Leverage	0.05	−0.16	−0.13	−0.08	1.00											1.05	0.95
(6) HHI	−0.01	0.10	0.12	−0.01	0.00	1.00										1.04	0.96
(7) R&D Expenditure	0.06	−0.25	−0.24	0.15	0.04	−0.06	1.00									1.22	0.81
(8) Corporate Firm	−0.06	0.29	0.23	−0.09	−0.05	0.05	−0.18	1.00								1.83	0.54
(9) Foreign Firm	0.06	−0.20	−0.17	0.02	0.05	−0.03	0.15	−0.61	1.00							1.62	0.61
(10) Customer Centricity	−0.02	−0.01	−0.00	0.03	−0.03	−0.00	0.00	0.00	−0.03	1.00						1.31	0.74
(11) International Market	−0.02	0.03	0.03	−0.00	−0.06	−0.00	−0.03	0.02	−0.00	0.18	1.00					1.17	0.85
(12) Environmental Sustainability	−0.06	0.02	0.02	0.02	0.02	0.00	−0.02	−0.01	0.03	0.00	0.12	1.00				1.08	0.92
(13) Product Innovation	−0.01	0.06	0.01	0.03	−0.04	−0.01	0.00	0.04	−0.00	0.46	0.31	0.11	1.00			1.80	0.55
(14) Firm size (log)	−0.18	0.41	0.35	−0.32	−0.08	0.15	−0.41	0.42	−0.26	−0.02	0.07	0.05	0.06	1.00		2.42	0.41
(15) Firm age (years)	−0.07	0.25	0.25	0.00	−0.13	0.00	−0.22	0.12	−0.12	0.01	0.10	0.09	0.13	0.06	1.00	1.22	0.82

Note: The table reports pairwise Pearson correlation coefficients for the variables used in the empirical analysis. Variance Inflation Factors (VIFs) and their reciprocals are also reported to assess potential multicollinearity. All VIF values remain below conventional thresholds, suggesting that multicollinearity is unlikely to affect the estimation results.

Table 5
Strategic priorities by AI users and non-AI users (row percentages).

Strategic Goal	AI Use	Value	Frequency	Row Percent
Customer Centricity	Non-AI Users	0	145	12.15
		1	1048	87.85
	AI Users	0	133	22.50
		1	458	77.50
International Market Orientation	Non-AI Users	0	329	27.58
		1	864	72.42
	AI Users	0	229	38.75
		1	362	61.25
Environmental Sustainability	Non-AI Users	0	695	58.26
		1	498	41.74
	AI Users	0	384	64.97
		1	207	35.03

Note: Row percentages are reported to show how the prevalence of each strategic priority differs between AI-using firms ($N = 600$) and non-AI firms ($N = 1200$). A value of 1 denotes that the firm reports the strategic goal on its website. The comparison illustrates that AI adopters and non-adopters do not share the same strategic profiles, underscoring the importance of considering strategy–AI complementarities in the empirical analysis.

Table 6
AI intensity and firm productivity.

	(1)	(2)	(3)	(4)
Variables	Productivity (Efficiency)			
AI Intensity (observed)	1.793***	1.791***		
	(0.618)	(0.614)		
Predicted AI Intensity			57.01**	56.74**
			(27.19)	(27.21)
Controls				
Log Revenue (t-1)	0.489***	0.489***	0.485***	0.485***
	(0.025)	(0.025)	(0.025)	(0.025)
Log Capital	−0.016	−0.017	−0.033	−0.033
	(0.026)	(0.026)	(0.027)	(0.027)
Log employment	0.125***	0.123***	0.630**	0.625**
	(0.037)	(0.037)	(0.253)	(0.253)
Log employment^2	−0.008**	−0.008**	−0.049**	−0.049**
	(0.003)	(0.003)	(0.021)	(0.021)
Log firm age	0.040**	0.039**	0.093***	0.093***
	(0.017)	(0.017)	(0.035)	(0.036)
Corporate Firm		0.036		0.038
		(0.031)		(0.031)
Foreign Firm		0.030		0.029
		(0.028)		(0.028)
HHI		0.019***		0.009
		(0.006)		(0.008)
Product innovation		0.026		0.024
		(0.029)		(0.029)
Constant	7.658***	6.854***	6.288***	5.874***
	(0.179)	(0.356)	(0.723)	(0.594)
Industry FE	YES	YES	YES	YES
Regional FE	YES	YES	YES	YES
Observations	1606	1606	1606	1606
R-squared	0.588	0.589	0.586	0.586

Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Note: The table reports estimates of the relationship between AI intensity and firm productivity. Columns (1) and (2) use observed AI intensity, while columns (3) and (4) employ predicted AI intensity obtained from the first-stage model to address potential endogeneity concerns. Industry and regional fixed effects are included in all specifications.

replace observed AI adoption with predicted AI values obtained in stage 1. By relying on predicted AI intensity, the analysis provides a more cautious assessment of its association with productivity and its interaction with firm strategies.

Columns (3) and (4) present the results of the model where predicted AI intensity is used to mitigate potential endogeneity concerns. The findings show that AI intensity is positively and significantly associated with firm productivity, suggesting that firms with higher levels of AI intensity tend to exhibit higher production efficiency. The estimated coefficient suggests that a one-unit increase in predicted AI intensity corresponds to roughly a 56-point improvement in production efficiency, holding other factors constant. It is important to interpret this magnitude considering the distribution of AI intensity in the sample. Since AI intensity is measured as the

Table 7
AI intensity, customer centricity and firm productivity

	(1)	(2)	(3)	(4)
Variables	Productivity (Efficiency)			
Predicted AI Intensity	55.35*	56.30**	55.60*	55.06**
	(28.37)	(28.47)	(28.40)	(28.04)
Customer centricity (CC)	−0.061*	−0.089**	−0.089**	−0.089***
	(0.031)	(0.035)	(0.035)	(0.035)
Predicted AI Intensity * CC	2.123	1.701	2.040	2.085
	(4.863)	(4.855)	(4.824)	(4.813)
Controls				
Log Revenue (t-1)	0.485***	0.486***	0.485***	0.485***
	(0.025)	(0.025)	(0.025)	(0.025)
Log Capital	−0.033	−0.034	−0.034	−0.034
	(0.027)	(0.027)	(0.027)	(0.027)
Log Employment	0.633**	0.640**	0.633**	0.628**
	(0.254)	(0.255)	(0.254)	(0.251)
Log Employment^2	−0.050**	−0.051**	−0.050**	−0.050**
	(0.021)	(0.021)	(0.021)	(0.021)
Log firm age	0.095***	0.091**	0.093**	0.092**
	(0.036)	(0.036)	(0.036)	(0.036)
HHI		0.010	0.009	0.010
		(0.008)	(0.008)	(0.008)
Product innovation		0.064*	0.061*	0.062*
		(0.033)	(0.033)	(0.033)
Corporate firm			0.037	0.037
			(0.031)	(0.031)
Foreign firm			0.026	0.026
			(0.028)	(0.028)
Leverage				0.0003
				(0.000)
Constant	6.310***	5.853***	5.887***	5.894***
	(0.726)	(0.594)	(0.595)	(0.590)
Industry FE	YES	YES	YES	YES
Regional FE	YES	YES	YES	YES
Observations	1606	1606	1606	1606
R-squared	0.587	0.588	0.588	0.588

Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Note: The table reports estimates examining whether customer-centric strategies moderate the relationship between AI intensity and firm productivity. The interaction term captures whether the productivity returns associated with AI intensity differ between customer-oriented and non-customer-oriented firms.

ratio of AI-related human capital to total employment and has a relatively low mean value, realistic changes in AI intensity imply more modest productivity gains. For instance, applying the estimated coefficient to an increase in AI intensity from the 25th to the 75th percentile corresponds to productivity improvements in the range of a few percentage points. This effect is economically meaningful and comparable to estimates found in recent research on digital technologies and productivity (e.g., Brynjolfsson et al., 2021; Czarnitzki et al., 2023). The positive association remains stable across model specifications, consistent with prior research that characterizes AI as a general-purpose technology associated with improved decision-making and process efficiency. Because AI intensity is constructed from the evolving stock of AI-related skills embedded in firms' workforce over time, these findings capture the productivity implications of changes in AI capabilities rather than a static adoption indicator. In line with earlier research, the result reflects the role of AI in improving forecasting, resource allocation, and operational optimization. Overall, the evidence supports the view that AI adoption is associated with measurable productivity gains even after accounting for firm size, capital, and market heterogeneity. The findings in Table 6 support our hypothesis that firms with greater AI intensity tend to achieve higher productivity; therefore, we accept Hypothesis 1.

4.2. *AI intensity, customer centricity, and firm productivity*

Table 7 reports the results in columns (1) through (4), which present estimates from the two-stage estimation approach testing the role of customer centricity as a complementary strategy to AI adoption. Across all four models, the coefficient for AI intensity remains positive and significant, confirming its robust association with firm productivity. By contrast, customer centricity is consistently associated with lower efficiency across specifications. The estimated coefficients suggest that firms pursuing a customer-centric strategic orientation exhibit productivity levels that are between 0.06 and 0.9 percentage points lower, depending on the specification. This suggests that while AI adoption is positively associated with firm productivity, a strong emphasis on customer needs may, in some cases, reduce operational efficiency.

Table 8
AI intensity, international market and firm productivity

	(1)	(2)	(3)	(4)
Variables	Productivity (Efficiency)			
Predicted AI Intensity	52.17*	52.29*	51.89*	51.28*
	(27.76)	(27.87)	(27.81)	(27.41)
International Market (IM)	−0.041*	−0.049**	−0.049**	−0.049**
	(0.024)	(0.025)	(0.025)	(0.025)
Predicted AI Intensity * IM	5.757*	5.780*	5.767*	5.834*
	(3.402)	(3.409)	(3.396)	(3.367)
Controls				
Log Revenue (t-1)	0.485***	0.486***	0.485***	0.485***
	(0.025)	(0.025)	(0.025)	(0.025)
Log Capital	−0.028	−0.028	−0.028	−0.028
	(0.028)	(0.028)	(0.028)	(0.027)
Log Employment	0.626**	0.628**	0.621**	0.615**
	(0.253)	(0.254)	(0.253)	(0.250)
Log Employment^2	−0.050**	−0.050**	−0.049**	−0.049**
	(0.021)	(0.021)	(0.021)	(0.021)
Log firm age	0.093***	0.091**	0.092**	0.092**
	(0.036)	(0.036)	(0.036)	(0.036)
HHI		0.010	0.010	0.010
		(0.008)	(0.008)	(0.008)
Product innovation		0.036	0.034	0.034
		(0.030)	(0.030)	(0.030)
Corporate firm			0.038	0.037
			(0.031)	(0.031)
Foreign Firm			0.028	0.028
			(0.028)	(0.028)
Leverage				0.0003
				(0.000)
Constant	6.335***	5.892***	5.925***	5.933***
	(0.727)	(0.603)	(0.604)	(0.598)
Industry FE	YES	YES	YES	YES
Regional FE	YES	YES	YES	YES
Observations	1606	1606	1606	1606
R-squared	0.587	0.587	0.588	0.588

Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Note: The table reports estimates examining whether international market orientation moderates the relationship between AI intensity and firm productivity. The interaction term captures whether firms pursuing international expansion experience different productivity returns from AI intensity relative to domestically focused firms.

All models show a positive relationship between firm revenue and firm productivity. The productivity of a firm is greatly influenced by its size (number of people), indicating an inverted U-shaped relationship, which shows that productivity increases with firm size up to a certain point, after which it declines. Furthermore, a positive and significant relationship exists between product innovation and firm productivity across all models.

Table 7 shows that while AI intensity remains positively related to productivity, customer-centric strategies on their own are associated with lower efficiency levels. The interaction between AI intensity and customer centricity is not statistically significant, suggesting that combining AI with customer-focused strategies does not yield additional productivity gains. One possible explanation lies in resource trade-offs: customer-centric approaches often require customization, flexible manufacturing systems, and complex data integration, which can raise costs and offset AI-related efficiency benefits (Huang & Rust, 2021). Moreover, in the Italian manufacturing context, many SMEs focus on product quality and relational marketing rather than data-driven personalization, which may limit the complementarity between AI and customer orientation. Overall, the findings indicate that while AI intensity is positively associated with productivity, its association is not automatically strengthened when coupled with customer-centric strategies. This result is consistent with evidence from human-capital and organizational research showing that performance gains from innovation-oriented strategies depend critically on firms' ability to manage coordination costs, human skills, and relational complexity, which may constrain the productivity impact of AI when customer responsiveness relies more on tacit knowledge and customization than on scalable data analytics. The results in Table 7 show that the interaction term between AI intensity and customer centricity is statistically insignificant. Therefore, we find no evidence supporting Hypothesis 2.

4.3. AI intensity, international market, and firm productivity

Table 8, Columns (1) through (4), presents four different models, all of which confirm the positive and significant relationship between AI intensity and firm efficiency. The relationship between AI intensity and international market strategy is consistently

Table 9
AI intensity, environmental sustainability and firm productivity

	(1)	(2)	(3)	(4)
Variables	Productivity (Efficiency)			
Predicted AI Intensity	53.94**	53.96*	53.62*	53.26*
	(27.47)	(27.56)	(27.51)	(27.27)
Environmental sustainability (ES)	−0.019	−0.021	−0.021	−0.021
	(0.025)	(0.024)	(0.025)	(0.025)
Predicted AI Intensity * ES	4.328	4.395	4.247	4.197
	(3.600)	(3.600)	(3.611)	(3.571)
Controls				
Log Revenue (t-1)	0.486***	0.486***	0.485***	0.486***
	(0.025)	(0.025)	(0.025)	(0.025)
Log Capital	−0.031	−0.032	−0.032	−0.031
	(0.028)	(0.028)	(0.028)	(0.028)
Log Employment	0.621**	0.622**	0.615**	0.612**
	(0.255)	(0.256)	(0.255)	(0.252)
Log Employment^2	−0.049**	−0.049**	−0.049**	−0.049**
	(0.021)	(0.021)	(0.021)	(0.021)
Log firm age	0.092***	0.090**	0.092**	0.092**
	(0.035)	(0.036)	(0.036)	(0.036)
HHI		0.011	0.010	0.010
		(0.008)	(0.008)	(0.008)
Product innovation		0.027	0.026	0.026
		(0.029)	(0.029)	(0.029)
Corporate firm			0.036	0.036
			(0.031)	(0.032)
Foreign firm			0.029	0.028
			(0.029)	(0.029)
Leverage				0.0002
				(0.001)
Constant	6.316***	5.849***	5.880***	5.885***
	(0.731)	(0.602)	(0.604)	(0.599)
Industry FE	YES	YES	YES	YES
Regional FE	YES	YES	YES	YES
Observations	1606	1606	1606	1606
R-squared	0.586	0.587	0.587	0.587

Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Note: The table reports estimates examining whether environmental sustainability strategies moderate the relationship between AI intensity and firm productivity. The interaction term assesses whether sustainability-oriented firms derive different productivity benefits from AI intensity than other firms.

positive and significant across all models, suggesting that firms combining international market strategies with higher AI intensity tend to exhibit higher productivity. The positive interaction coefficient, ranging from approximately 5.76 to 5.83 across specifications, indicates that the association between AI intensity and productivity is stronger among internationally oriented firms.[10] Interpreted in practical terms, this association reflects the fact that AI adoption disproportionately benefits firms operating in data-intensive international environments. Given average AI intensity levels in the sample, the interaction implies productivity gains of approximately 2–3% for internationally oriented firms, which is substantial in the context of manufacturing productivity growth. These gains are plausibly driven by improvements in demand forecasting, logistics coordination, and market selection rather than by scale effects alone. Conversely, international orientation alone is not associated with the same productivity advantages observed among firms combining internationalization and AI intensity. The results are consistent with the view of AI as a general-purpose technology that may help firms utilize large datasets for more efficient targeting of international markets. Therefore, the evidence supports Hypothesis 3, suggesting that the combination of AI intensity and international market strategies is positively associated with firm productivity.

As for controls, the coefficient of (lagged) firm revenue is significant and has a positive relationship with firm productivity. There is a positive and significant inverted U-shaped association between firm size and firm productivity, indicating that larger firms tend to exhibit higher productivity up to a certain threshold, beyond which productivity is associated with diminishing returns to additional increases in firm size.

[10] It is important to contextualize the magnitude of the interaction effect. Because AI intensity is a normalized measure with mean values close to zero (reflecting the limited share of AI-skilled workers in most firms), the numerical coefficient of the interaction term appears large. However, multiplying the interaction coefficient (≈5.8) by the average level of AI intensity (≈0.004) yields an implied productivity gain of about 2–3% - an economically plausible effect for firms combining AI capabilities with export-oriented strategies. This interpretation aligns with recent empirical studies documenting moderate but meaningful productivity gains from digital capability accumulation.

Results in Table 8 show that AI intensity is positively and significantly associated with the productivity of firms pursuing international market strategies. The positive and significant interaction term suggests that firms with an international market orientation are better positioned to realize productivity gains associated with AI intensity, potentially due to the greater importance of information processing, forecasting, and coordination in international markets. This finding supports the view that AI may operate as a capability multiplier in data-intensive environments such as export markets, enabling better forecasting, logistics optimization, and cross-border coordination. The result is consistent across specifications, confirming robust complementarities between AI use and international expansion. Overall, these findings suggest that AI adoption provides a tangible advantage for firms competing internationally by improving both strategic decision-making and operational performance. The evidence in Table 8 therefore supports Hypothesis 3.

4.4. *AI intensity, environmental sustainability, and firm productivity*

Table 9, columns (1) to (4), shows that AI intensity is positively and significantly associated with firm productivity, a result which is consistent with the previous evidence. This reinforces the idea that firms investing in artificial intelligence tend to achieve higher levels

Table 10
Robustness check using Total Factor Productivity (TFP) as dependent variable.

	(1)	(2)	(3)	(4)
Variables	TFP	TFP	TFP	TFP
Predicted AI Intensity	52.03*	49.12*	46.82*	49.41*
	(28.21)	(29.42)	(28.61)	(28.67)
Strategy				
Customer centricity (CC)		−0.099***		
		(0.036)		
International Market (IM)			−0.049*	
			(0.026)	
Environmental sustainability (ES)				−0.019
				(0.025)
Interactions				
Predicted AI Intensity * CC		3.824		
		(5.125)		
Predicted AI Intensity * IM			5.951*	
			(3.425)	
Predicted AI Intensity * ES				3.852
				(3.544)
Controls				
Log Revenue (t-1)	0.501***	0.501***	0.501***	0.501***
	(0.026)	(0.026)	(0.026)	(0.026)
Log Capital	−0.141***	−0.142***	−0.136***	−0.140***
	(0.027)	(0.027)	(0.028)	(0.027)
Log Employment	0.412	0.418	0.406	0.405
	(0.261)	(0.262)	(0.261)	(0.263)
Log Employment^2	−0.043**	−0.044**	−0.044**	−0.042*
	(0.022)	(0.022)	(0.022)	(0.022)
Log firm age	0.076**	0.075**	0.076**	0.075**
	(0.036)	(0.036)	(0.036)	(0.036)
Corporate firm	0.019	0.019	0.019	0.017
	(0.026)	(0.026)	(0.026)	(0.026)
Foreign firm	−0.019	−0.019	−0.019	−0.018
	(0.025)	(0.025)	(0.025)	(0.025)
HHI	−0.022**	−0.022**	−0.022**	−0.021**
	(0.009)	(0.009)	(0.009)	(0.009)
Product innovation	0.019	0.058*	0.029	0.020
	(0.030)	(0.035)	(0.031)	(0.030)
Leverage	0.012	0.012	0.012*	0.011
	(0.007)	(0.007)	(0.007)	(0.007)
Constant	−2.174***	−2.156***	−2.121***	−2.173***
	(0.624)	(0.626)	(0.632)	(0.632)
Industry FE	YES	YES	YES	YES
Region FE	YES	YES	YES	YES
Observations	1617	1617	1617	1617
R-squared	0.385	0.387	0.387	0.385

Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Note: TFP is computed as the residual from a Cobb–Douglas production function regressing log value added on log capital and log employment, including industry and regional fixed effects. The models replicate the main specifications reported in Tables 6–9, replacing labor productivity with TFP. Standard errors are robust to heteroskedasticity. Coefficients on AI intensity and interaction terms remain directionally consistent with the main results.

of production efficiency.

However, the coefficients for environmental sustainability and its interaction with AI intensity are not statistically significant across any of the models. This suggests that, within Italian manufacturing, the association between AI intensity and productivity does not appear to be significantly strengthened by environmental sustainability strategies. In other words, while AI intensity is positively associated with productivity, its joint use with sustainability objectives does not appear to generate short-term economic returns.

Several contextual factors may help explain this result. First, many AI-driven sustainability initiatives—such as emission monitoring, waste reduction, and energy optimization—are still in the early phases of experimentation. These projects often require substantial upfront investments in digital infrastructure, data integration, and employee training, and their benefits may take longer to materialize. Second, environmental actions in Italy are often shaped by regulatory compliance and social responsibility rather than being fully embedded into firms' operational strategies. In such contexts, sustainability-related investments may primarily serve compliance, legitimacy, or reputational objectives rather than efficiency-enhancing ones. Prior evidence from dynamic business environments suggests that firms may adopt formal sustainability practices even when these do not translate into immediate productivity gains, especially when regulatory and institutional pressures dominate economic incentives. Third, our measure of environmental sustainability is derived from website-based textual analysis. While this approach provides large-scale coverage, it may not capture the depth or intensity of sustainability integration within firms, possibly leading to an underestimation of its effects.

Another possible explanation relates to the trade-offs between environmental objectives and production efficiency. Implementing greener processes can sometimes increase production costs in the short term, particularly for small and medium-sized firms with limited financial and technological resources. This tension between sustainability and productivity is consistent with prior evidence suggesting that the economic benefits of environmentally oriented innovation emerge only when firms achieve sufficient scale and technological maturity.

Overall, these findings highlight that the productivity effects of AI are not uniform but depend strongly on the strategic and organizational context in which they are deployed. Firms may deploy AI in support of sustainability goals whose benefits emerge over longer time horizons or extend beyond immediate productivity outcomes. The evidence in Table 9 therefore does not support Hypothesis 4, indicating that the combination of AI adoption and environmental sustainability objectives has not yet produced measurable improvements in productivity among Italian manufacturing firms.

4.5. *Robustness checks*

To assess the stability of the main findings, we conducted a series of robustness checks. We began by re-estimating the baseline models using alternative sets of controls. Across all specifications, whether including or excluding firm-level financial variables, ownership dummies, and market concentration, the coefficients on AI intensity and the interaction terms remained similar in sign and magnitude. This indicates that the results are not driven by the particular choice of controls.

As a second step, we replaced labor productivity (value added per employee) with a measure of Total Factor Productivity (TFP). TFP was computed as the residual from a Cobb–Douglas production function regressing log value added on log capital and log employment, including industry and regional fixed effects (see appendix table A8). We then used this TFP residual as the dependent variable in the full two-stage estimation approach. Table 10 shows the results. AI intensity remains positive and statistically significant across all specifications, and the patterns for customer centricity, international orientation, and environmental sustainability mirror those in the main productivity models. This confirms that the findings are not sensitive to the choice of productivity measures.

Taken together, these robustness checks show that the core results, namely, the positive association between AI intensity and productivity, the negative relationship between customer centricity and efficiency, the strong complementarities with international market orientation, and the absence of a significant link for environmental sustainability - are consistent across alternative specifications, subsamples, and outcome measures. Moreover, these robustness checks reinforce the credibility of the empirical findings and suggest that the observed patterns reflect stable relationships rather than artefacts of model specification, variable construction, or measurement choices.

5. Conclusion

This paper contributes to the literature on strategy and innovation by examining the implications of investment in artificial intelligence (AI) for firm productivity, with particular attention to how AI interacts with three strategic orientations: environmental sustainability, customer centricity, and international market expansion.

To address our research questions, we compiled a comprehensive dataset of 1800 Italian manufacturing firms by integrating information from several sources. LinkedIn profiles provided data on employee skills, which we used to construct a measure of firms' AI intensity. Company websites offered evidence on strategic objectives and innovation activities, while financial information was obtained from Moody's BvD-Amadeus database. With this dataset, we estimated an augmented Cobb–Douglas production function using a two-stage estimation approach, examining both the direct effect of AI intensity on productivity and its interaction with different firm strategies.

This paper presents four main findings. First, firms with higher levels of AI intensity tend to exhibit higher productivity in their production processes. By leveraging large volumes of data, these firms improve decision-making more efficiently and cost-effectively, thereby generating greater output. This aligns with Cockburn et al. (2018), who highlight AI as a general-purpose technology that enhances predictive decision-making. By using big data and algorithms to evaluate outcomes, firms can reduce expenses, increase efficiency, and stimulate innovation in product development.

Second, the interaction between customer centricity and AI intensity is not statistically significant. Moreover, customer centricity on its own is negatively associated with productivity. This suggests that firms emphasizing customer orientation without effectively integrating AI may face efficiency losses, as customization requires complex supply chain management and flexible manufacturing systems. Prior research (Pine et al., 1993) has noted that while mass customization can provide competitive differentiation, it often increases operational complexity and costs, which may offset AI-driven efficiency gains.

Third, we find strong complementarities between AI intensity and international market expansion. Firms that combine higher AI intensity with an internationalization strategy tend to exhibit significantly higher productivity. AI enables firms to identify promising foreign markets, align products with international demand, and optimize distribution. For instance, AI tools improve delivery efficiency and product distribution through real-time data (Oguejiofor et al., 2023; Osman, 2019).

Finally, we observe no significant relationship between environmental sustainability strategies and productivity. Likewise, the interaction between AI intensity and environmental sustainability is not statistically significant, suggesting no measurable difference in productivity outcomes for firms pursuing environmental sustainability objectives.

Among the three strategic orientations examined, international market expansion appears to provide the most favorable environment for translating AI capabilities into productivity gains. International operations involve complex information-processing requirements related to market selection, demand forecasting, logistics coordination, pricing decisions, and cross-border supply-chain management. These activities are highly data intensive and therefore particularly compatible with AI-enabled analytical capabilities. By contrast, customer-centric and sustainability-oriented strategies rely more heavily on tacit knowledge, organizational adaptation, stakeholder management, and non-economic objectives, reducing the immediate productivity returns associated with AI deployment.

By examining how firms integrate artificial intelligence (AI) with different strategies, this study advances research on the intersection of digital transformation, strategy, and productivity. Prior studies have emphasized the role of AI as a general-purpose technology that enhances decision-making and efficiency (Cockburn et al., 2018), as well as its potential in enabling market segmentation and global competitiveness (Pine et al., 1993). Our study extends these contributions by systematically analyzing how AI intensity interacts with three distinct strategic goals: customer centricity, international market expansion, and environmental sustainability, using a unique dataset of Italian manufacturing firms. Methodologically, the study contributes by integrating three complementary sources of firm-level information: LinkedIn employee profiles, web-scraped evidence on firm strategic orientations, and financial records from the Amadeus database. This multi-source design allows us to connect AI-related human capital, strategic priorities, and productivity outcomes within a unified empirical framework. In addition, our measure of AI intensity captures the evolving stock of AI-related skills embedded within firms, providing a dynamic and capability-based indicator of AI adoption that moves beyond conventional binary measures of technology use. The findings show that while AI intensity is positively associated with productivity, these associations vary across firm strategic goals. The positive association between AI intensity and productivity is stronger among firms with an international market orientation, whereas no significant interaction effects are observed for environmental sustainability or customer-centric strategies. These results enrich the strategy and innovation literature by highlighting that the productivity payoffs of AI are contingent on the broader strategic context. In doing so, the study integrates perspectives from the resource-based view and dynamic capabilities theory, illustrating how firms can align AI investments with strategic goals to unlock productivity gains.

Taken together, these results suggest that the association between AI intensity and firm performance is not uniform but varies according to firms' strategic orientations and organizational capabilities. In the Italian manufacturing context, productivity gains from AI appear strongest when firms use it to enhance data-driven decision-making and international competitiveness, while its role in customer-focused and sustainability-oriented strategies remains less mature. These findings point to the need for further research into the temporal and contextual dynamics of AI adoption, including longitudinal studies to capture delayed effects and comparative analyses across sectors or countries. By highlighting both the potential and the boundaries of AI-driven transformation, this study contributes to a more nuanced understanding of how strategic orientation shapes the economic value of digital technologies.

From a managerial perspective, firms should approach AI adoption not as an isolated technological investment but as a strategic capability that requires alignment with broader business objectives. Managers can enhance the effectiveness of AI by developing complementary human and organizational skills, establishing cross-functional coordination between digital and strategic teams, and carefully evaluating cost–benefit trade-offs when applying AI in customer-oriented or sustainability-focused areas. For policymakers, the findings highlight the importance of supporting AI diffusion through targeted incentives, training programs, and investments in digital infrastructure, particularly to help small and medium-sized enterprises integrate AI into their strategic planning. Together, these practical implications reinforce the study's central insight: the value of AI depends not only on adoption itself, but on how it is embedded within firms' strategic and institutional contexts.

6. Future research

Further research should continue to examine the strategic contingencies that shape the productivity returns from AI adoption. In particular, longitudinal analyses could provide more robust causal evidence and deeper insights into the relationship between AI intensity, firm outcomes, and strategic orientations. Moreover, examining differences across sectors and regions would allow policymakers to develop a more comprehensive understanding of how firms adopt AI technologies in pursuit of their strategic objectives. This study provides a foundation for both policymakers and managers to better grasp the role of artificial intelligence in the manufacturing industry and its interaction with firm strategies aimed at achieving diverse objectives. Future studies could also examine how the benefits of AI evolve over time and under different implementation models, particularly in contexts where digital capabilities and sustainability goals are still developing. Incorporating qualitative case studies or mixed methods could offer richer insights into how managers integrate AI into strategic decision-making and balance efficiency with long-term goals. Cross-country comparisons would further clarify how institutional and policy differences shape the strategic value of AI investments.

7. Limitations

This paper provides valuable insights into AI intensity, firm strategies, firm productivity, and the use of website data. Nevertheless, the study is limited to Italian manufacturing firms. The specific economic, innovation, and cultural context of Italy may influence the extent to which our findings are applicable to other countries or regions. Comparative analyses across different national and sectoral contexts could therefore generate important additional insights. Moreover, while our AI-intensity measure captures the accumulation of AI-related skills over time, the empirical analysis remains firm-level in nature. Future research using panel data could provide deeper insights into the dynamic relationship between AI adoption, firm strategies, and productivity outcomes. A further limitation concerns the distinction between AI capability accumulation and actual AI utilization. While employee skills provide valuable information regarding firms' AI-related competencies, they do not necessarily indicate the extent to which AI tools are effectively deployed in operational decision-making. Consequently, our AI-intensity measure should be interpreted primarily as a proxy for AI capability rather than direct AI usage. Moreover, although AI intensity is constructed from longitudinal employee-level information, the empirical design remains primarily cross-sectional. Future research could exploit fully longitudinal firm-level panels to examine the causal evolution of AI capabilities and productivity over time. Finally, while the present study concentrates on environmental, customer-centric, and internationalization strategies, extending the analysis to other strategic orientations would further deepen the understanding of how AI intensity affects firm productivity. In addition, the study's reliance on publicly available LinkedIn and website data, while innovative, may introduce selection and reporting biases. Firms more active online could appear more digitally advanced than they actually are, while others may underreport strategic orientations. Although the analysis controls for industry and regional effects, unobserved heterogeneity in managerial practices or digital maturity may still influence the results. Future research should therefore combine digital trace data with survey or qualitative evidence to validate and enrich these findings.

CRediT authorship contribution statement

Syed Muhammad Ali Shah: Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Marco Cucculelli:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Conceptualization.

Informed consent statement

Not applicable. This study did not involve human participants or identifiable personal data.

Ethics statement

This study did not involve human participants, human biological materials, animals, or any procedures requiring approval by an institutional ethics committee. Therefore, ethical approval was not required for this research.

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The authors declare that they have no competing financial interests, personal relationships, or professional affiliations that could have influenced the research, authorship, and/or publication of this article.

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Appendix A. The BERT Algorithm

BERT, also known as Bidirectional Encoder Representations for Transformers, is a language model that was created by Devlin

(2018). A Natural Language Processing (NLP) model employs neural network architectures to process textual information.[11] In text analysis, the meaning of a single word varies depending on the context in which it is used. The BERT model's attractiveness lies in its ability to generate multiple consecutive iterations of embeddings. Each new iteration incorporates all the embeddings from the prior iteration.[12] Transformers learn every term that is most suited by using a trial-and-error approach. Transformer takes a well-written sentence that already exists, hides some words at random, and then asks BERT to find the words that are hidden (Liu, Lin, Shi, & Zhao, 2021). Then, using its vocabulary to identify the disguised word, BERT predicts the probability of each word. The model's capacity to recover a masked word in the following iteration is enhanced by computing an error based on the guess's accuracy. To train the entire model, an enormous quantity of data is required because each improvement is marginal. In fact, millions of phrases taken from Wikipedia and Book Corpus (which include 800 and 2500 million words, respectively) have been used to train BERT. As a result, BERT gained a comprehensive understanding of the language that embeddings use and summarize. The model used in this procedure is known as BERT, and it is a semi-supervised learning stage. The important thing about the BERT model is that, once everything is done, it also demonstrates the model's accuracy and how well it divides up the skills into several categories. Currently, it is the most significant algorithm that simultaneously captures the performance.

Table A1
AI Intensity in manufacturing firms and sample firms' distribution by Italian regions.

Region	Firm Size			Total Firms	Average Regional AI Intensity
	Small	Medium	Large		All firms
Abruzzo	06	03	10	19	0.0001693
Basilicata	02	00	00	02	0.0000001
Calabria	04	00	00	04	0.0008008
Campania	26	19	08	53	0.0058558
Emilia Romagna	102	168	93	363	0.0058451
Friuli Venezia Giulia	16	23	16	55	0.0043157
Lazio	55	30	33	108	0.0104966
Liguria	17	14	05	36	0.0094821
Lombardia	160	191	165	510	0.0184835
Marche	19	14	12	45	0.0044469
Piemonte	40	37	43	120	0.0015535
Puglia	10	06	09	25	0.0002745
Sardegna	00	02	00	02	0.0000002
Sicilia	10	04	02	16	0.0000389
Toscana	47	36	26	109	0.0035435
Trentino Alto Adige	05	07	05	17	0.0041819
Umbria	05	00	04	09	0.0018704
Veneto	74	69	51	194	0.0042758
Total	635	621	544	1800	

Note: This table shows the number of firms by Italian region and firm-size (small: <50 employees; medium: 50–249; large: ≥250) together with the average AI intensity, measured as AI stock divided by total employees. The sample includes firms from all major Italian regions and across all size categories. Regional averages are consistent with the overall composition of the Italian manufacturing sector (ISTAT, 2023).

Table A2
Industrial distribution (Manufacturing sector) (AI and Non-AI).

ATECO code	Industrial Group	Total firms	AI- Firms	Non-AI Firms
10	Manufacture of food products	73 (4.06%)	25 (4.17%)	51 (4.25%)
11	Manufacture of beverages	09 (0.50%)	03 (0.50%)	06 (0.50%)
12	Manufacture of tobacco products	02 (0.11%)	01 (0.17%)	01 (0.08%)
13	Manufacture of textiles	27 (1.50%)	09 (1.50%)	18 (1.50%)
14	Manufacture of wearing apparel	33 (1.83%)	11 (1.83%)	22 (1.83%)
15	Manufacture of leather and related products	16 (0.89%)	05 (0.83%)	11 (0.92%)
16	Manufacture of wood and products of wood and cork	09 (0.50%)	03 (0.50%)	06 (0.50%)
17	Manufacture of paper and paper products	24 (1.33%)	08 (1.33%)	16 (1.33%)
18	Printing and reproduction of recorded media	17 (0.94%)	06 (1.00%)	12 (1.00%)
19	Manufacture of coke and refined petroleum products	06 (0.33%)	02 (0.33%)	04 (0.33%)

(*continued on next page*)

[11] Text data refers to information that is recorded and saved in the textual format. It can involve several forms of written expression, such as social media posts, comments, informational content, or any type of blog that is conveyed by words rather than numerical data.

[12] BERT performs twelve iterations, which is a trade-off between the model's size and its efficiency. Based on empirical evidence, it is generally observed that having more layers tends to result in a higher understanding. In the BERT model, the term "bidirectional" means that it pays attention to both the left and right sides of the sentence. This contrasts with other models, such as Recurrent Neural Networks or GPT, which only consider preceding words.

Table A2 (*continued*)

ATECO code	Industrial Group	Total firms	AI- Firms	Non-AI Firms
20	Manufacture of chemicals and chemical products	73 (4.06%)	24 (4.00%)	50 (4.17%)
21	Manufacture of pharmaceutical products and preparations	50 (2.78%)	16 (2.67%)	34 (2.83%)
22	Manufacture of rubber and plastic products	50 (2.78%)	17 (2.83%)	34 (2.83%)
23	Manufacture of other non-metallic mineral products	43 (2.39%)	16 (2.67%)	30 (2.50%)
24	Manufacture of basic metals	31 (1.72%)	17 (2.83%)	22 (1.83%)
25	Manufacture of fabricated metal products (except machinery and equipment)	167 (9.28%)	51 (8.50%)	116 (9.67%)
26	Manufacture of computer, electronic and optical products	326 (18.11%)	107 (17.83%)	219 (18.25%)
27	Manufacture of electrical equipment	118 (6.56%)	40 (6.67%)	78 (6.50%)
28	Manufacture of machinery and equipment n.e.c.	411 (22.83%)	140 (23.33%)	271 (22.58%)
29	Manufacture of motor vehicles, trailers and semi-trailers	62 (3.44%)	22 (3.67%)	40 (3.33%)
30	Manufacture of other transport equipment	55 (3.06%)	19 (3.17%)	36 (3.00%)
31	Manufacture of furniture	21 (1.17%)	07 (1.17%)	15 (1.25%)
32	Other manufacturing	30 (1.67%)	11 (1.83%)	21 (1.75%)
33	Repair and installation of machinery and equipment	133 (7.39%)	46 (7.67%)	87 (7.25%)
	Total	**1800**	**600**	**1200**

Note: The table reports the distribution of firms across two-digit ATECO manufacturing industries. Percentages are calculated relative to the total number of firms in each column. The similarity between AI and non-AI firms across industries suggests that the sample is not concentrated in a limited number of sectors.

Table A3

First-stage regression: Determinants of AI intensity.

	(1)	(2)	(3)	(4)
	First-Stage			
Variables	AI Intensity			
R&D Expenditure	−6.27e-05	2.68e-05	−9.74e-05	4.45e-05
	(0.000102)	(0.000114)	(0.000118)	(0.000122)
Log capital	0.00236*	0.00212*	0.00222*	0.00190
	(0.00127)	(0.00124)	(0.00125)	(0.00124)
Log employee	−0.00292***	−0.00235***	−0.00291***	−0.00231***
	(0.000868)	(0.000553)	(0.000878)	(0.000538)
Log firm age	−0.00142	−0.00178**	−0.00138	−0.00174**
	(0.00104)	(0.000838)	(0.00106)	(0.000854)
Constant	0.0177***	0.0114***	0.0148***	0.0120***
	(0.00388)	(0.00355)	(0.00391)	(0.00426)
Industry FE	NO	YES	NO	YES
Region FE	NO	NO	YES	YES
Observations	1646	1646	1646	1646
R-squared	0.037	0.595	0.046	0.602

Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Note: The table reports first-stage estimates used to generate predicted AI intensity. Predicted values from column (4) are employed in the second-stage productivity models. Industry and regional fixed effects are included as indicated.

Table A4

List of AI-related skills – Examples for selected skills.

AI Skills				
Tableau	Generative AI	Meta Learning	Natural Language Processing (NLP)	Alation Data Catalog
Machine learning	Neuro-Linguistic Programming	Association Rule Learning	Image Processing	Chatbot
Genetic Programming	Unsupervised Learning	Forecasting Models	Convolutional Neural Networks (CNN)	Facial Recognition
Robotics	Machine Learning Algorithms	federated learning	Scikit-Learn	Knowledge-based System
Apache Spark	Packet Tracer	Predictive Analysis	Speech Recognition	Hidden Markov Model
TensorFlow	Process Automation	Text Mining	Supervised Learning	Named Entity Recognition
Deep Learning	Xgboost	Cloud computing	Algorithmic Trading	Syman
Artificial Neural Networks	Algorithm Analysis	Deep Learning architecture	Classification and Regression Tree (CART)	Network Traffic Analysis
Computer Vision	Quantum Mechanics	Rapid Learning	Feature Learning	Robotic Process Automation (RPA)
Boosting	Association Rule Learning	text analysis	Eye Tracking	Reinforcement learning

Note: The table presents illustrative examples of skills classified as AI-related by the BERT-based classification model. The complete classification dictionary contains a broader set of AI skills identified from employee profiles.

Table A5
List of technical skills – Examples for selected skills.

Technical Skills				
CSS	SAS Macro Language	PHP	Microsoft CRM	Core Java
WordPress	Java Server Pages (JSP)	CVS	PyCharm	COBIT
Business Analysis	Software Architectural Design	TCP/UDP	CQRS	Topcat
Graphics Software	Oracle Database	Red Hat Linux	HTML & JS	Adobe Bridge
Software Development	CAD/CAM	HiveQL	Sound Design	API Testing
Microsoft SQL Server	Blockchain	Jasper Report	Fortran 90	IoT Hub
CORBA	Application Monitoring	Cloud Storage	Switching	C++ Programming
JBoss Application Server	JavaScript Frameworks	Scripting	Jupiter	Dublin Core
Raspberry Pi	Software Testing	IT security	3D Graphics	3D Geometry
CFD	IT Security Operations	Software ERP	SAP NetWeaver	CLP

Note: The table presents illustrative examples of technical skills used in the employee-skill classification procedure. These skills represent technical competencies that support, but do not directly constitute, AI-related expertise.

Table A6
List of soft skills – Examples for selected skills.

Soft Skills				
Team building	Project Planning	Product Marketing	Strategic Leadership	Stress Management
Public speaking	Social Networking	Course planning	Negotiation	Diplomacy
Teaching	Media Relations	Team Motivation	Influence	Goal Setting
Project Coordination	Photography	Reporting	Positivity	Integrity
Regulatory Affairs	Lead Generation	Perception	Empathy	Delegation
Creativity Skills	Art Direction	Report Writing	Flexibility	Relationship Building
Acting	Creative Writing	Ethics	Interpersonal Skills	Analytical Skills
Business plan	Strategy and Marketing	Team Mentoring	Collaboration	Attention to Quality
Consulting	Swimming	Employee Training	Time Management	Cross-Culture Communication
Customer Satisfaction	Coaching	Presentations	Persuasion	Leadership Development

Note: The table presents illustrative examples of soft skills identified within employee profiles. These skills capture interpersonal, managerial, and organizational capabilities relevant to workplace performance.

Table A7
AI-intensity scores – Examples for selected companies in the sample.

No	Job Title	Employer	Skills	Score	Normalized
1	Machine Learning engineer	Firm A	Machine learning (0.012), Artificial intelligence (0.003), Deep learning (0.004), Natural language Processing (0.0014), Python (0.0036), 'Image Processing (0.0017), TensorFlow (0.0024), Pytorch (0.0016), Scikit-learn (0.0010), Computer Vision Recommender systems (0.00025), Software Development (0.0060), Algorithms (0.0028) Predictive Modeling (0.0003), Pattern Recognition (0.001), Scrum (0.002), Apache Spark (0.0009), Back-end Web Development': (0.0002)	0.037	0.87
2	Computer Vision Engineer	Firm B	Computer Vision (0.004,) Python (0.0036) Deep Learning (0.0043), Simulations (0.0011) Machine Learning (0.012) Image Processing (0.0018), TensorFlow (0.0024), Algorithms (0.0028), Deep Neural Networks (0.0002), Neural Networks (0.00123), Mongodb (0.0023), GitHub (0.00128), Convolutional Neural Networks (0.00048), Artificial Intelligence (0.0035) Latex (0.0048)	0.035	0.83
3	Senior AI Engineer	Firm C	Machine Learning (0.012), Google Cloud Platform (0.00054) NumPy (0.0010), OpenCV (0.0018), Convolutional Neural Networks (0.00049), Mlops (0.00012), Agile Methodologies (0.0018), Mathematics (0.00065), Artificial Intelligence (0.0034), Computer Vision (0.0041), Test Driven Development (0.00056), Deep Learning (0.0043), TensorFlow (0.0024), Jupyter (0.00022), Pandas (0.00063), Git (0.0060), Google Bigquery (0.00011)	0.034	0.81
4	Senior Algorithm Engineer	Firm D	Machine learning (0.020), Reinforcement Learning (0.00040), Tensorflow (0.0024), 'Artificial Intelligence (0.0034), Unity3d (0.00044), Ros (0.00043), Computer Vision (0.0041), Recommender Systems (0.00025), Deep Learning (0.0043), Algorithms (0.0028), Image processing (0.0018), Image Analysis (0.00017) Software Development (0.0060), Robotics (0.0012), Python (0.0036), C Programming Language (0.00088)	0.028	0.66
5	NLP Engineer and R&D Engineer	Firm E	Artificial intelligence (0.0034), Openoffice (0.00010), Software (0.00026), Matlab (0.0076), Virtual reality (0.00016), Mathematics (0.00065), Tutoring (0.00014), Machine learning (0.012), Natural Language Processing (0.0015), Python (0.0036), Career Management': (0.000044)	0.019	0.46
6	Data Analyst	Firm F	Data science (0.0028), Project Management (0.011), Microsoft Excel (0.0068), Strategy (0.0009), Analytical Skills (0.0011), Python (0.0036), Pandas (0.00063), R-software (0.0029), SQL (0.016), Tableau (0.0010), Data Analysis (0.0038),	0.022	0.52

(*continued on next page*)

Table A7 (*continued*)

No	Job Title	Employer	Skills	Score	Normalized
7	Senior Data Scientist	Firm G	Machine Learning (0.012), Data Mining (0.0038), Teamwork (0.0025), Data Visualization (0.0011), Engineering (0.0015), Big Data (0.0031), Data Science (0.0028), Javascript (0.012), Artificial Intelligence (0.0034), Business Intelligence (0.0029), Big Data (0.003), Programming (0.0037), Statistical Modeling (0.00045), Machine Learning (0.012), Data Analysis (0.0034), 'Data Warehouse (0.00080), SQL (0.016), R-Software (0.0029), Statistics (0.0016), Mathematics (0.00065), Programming (0.00015), Data Mining (0.0038), Business Objects (0.00027), Team Work (0.00014), Problem Solving (0.0064),	0.021	0.50
8	Cloud Architect, Driving Innovation and Data Excellence	Firm H	Machine Learning (0.012), Web Development (0.0026), SQL (0.016), Data Analysis (0.0038), Databases (0.0026), MySQL (0.0098), Data Science (0.0028), Apache Spark (0.00095), Business Intelligence (0.0029), Java Enterprise Edition (0.0033), Hibernate (0.0022), Semantic Web (0.0005), GWT (0.00016), Eclipse (0.0049), Latex (0.0048), Spring (0.0010), Computer Science (0.0026), Algorithms (0.0028), Software Engineering (0.0035), Microservices (0.0006), Back-End Web Development (0.00024)	0.028	0.65
9	Big Data engineer	Firm I	Software development (0.0060), MySQL (0.0098), Git (0.0060), Analytical Skills (0.0011), Java (0.015), Machine Learning (0.012), Cybersecurity (0.00043), Data Analysis (0.0038), SQL (0.016), Artificial Intelligence (0.0034) Data Structures (0.00031), Computer Engineering (0.00015), OOP (0.00168), Personal Finance (0.0000092)	0.015	0.36
10	Head of Data Science & AI	Firm J	Data Science (0.0028), Machine Learning (0.012), Data Engineering (0.00034), Program Management (0.0012) Agile Methodologies (0.0018), Algorithms (0.0028), Artificial Intelligence (0.0034), Business Intelligence (0.0029), Big Data (0.003) Data Modeling (0.0011), Data Visualization (0.0011), Data Warehousing (0.00076), Data Analysis (0.00378), Software Engineering (0.0035), Enterprise Architecture (0.00098), Web Applications (0.0018), Business Development (0.0017), Telecommunications (0.0010), Node.js (0.0020), SQL (0.016), Team Leadership (0.0029), Big Data Analytics (0.00048), Natural Language Processing (0.0015), Google Cloud Platform (0.00054), Web Scraping (0.00017), Robotic Process Automation (0.00015), Business Analysis (0.0017)	0.023	0.55

Note: The table provides illustrative examples of employee profiles, associated skill sets, and corresponding AI-intensity scores. Firm names have been anonymized (Firm A–Firm J) to preserve confidentiality. Scores are calculated using the weighted classification framework described in Section 3.2 and are subsequently normalized to facilitate comparison across profiles. The examples are presented solely to illustrate the scoring procedure and do not represent the full distribution of AI-intensity scores within the sample.

Table A8
First-stage regression for TFP residual construction.

	Model 1
Variables	Log value added
Log capital	0.0535***
	(0.0101)
Log employment	1.065***
	(0.0176)
Constant	2.789***
	(0.257)
Industry FE	YES
Region FE	YES
Observations	1659
R-squared	0.940

Robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Note: The table reports the Cobb–Douglas production function used to construct the TFP residual employed in the robustness analysis. The estimated residual captures firm productivity after accounting for labor and capital inputs, together with industry and regional fixed effects.

Data availability

Data will be made available on request.

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