Bridging IT Workers and Domain Experts: The Changing Role of Managers in AI Era

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Abstract

Utilizing artificial intelligence (AI) often requires inputs of both domain expertise and IT skills. To facilitate this, firms need to form interdisciplinary teams composed of domain experts and IT engineers. However, this approach can lead to potential communication frictions and teamwork challenges. This paper examines how firms modify managers' skill sets to bridge the gap between domain experts and IT engineers and encourage effective collaboration. By analyzing over ten million job postings, we track the changes in managers' skills alongside firms' AI adoption. Our findings indicate that an increase in AI adoption within firms is likely to increase the inclusion of collaboration and software skills in managerial job posting requirements. More specifically, a ten percentage-point increase in the proportion of AI job postings corresponds to a 0.24 percentage-point increase in the likelihood that managerial job postings will demand collaboration skills, and a 0.21 percentage-point rise in software skill requirements. These effects are more pronounced in large and non-IT firms, as well as firms located near AI-strong universities. Moreover, these trends are primarily observed for managers responsible for team formation and development, and are moderated by the firm's corporate culture. We conclude that firms are changing managers' skills in response to the frictions between IT workers and domain experts.

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Firms are increasingly adopting artificial intelligence (AI) as a key driver for innovation and productivity growth (Babina et al. 2024; Zolas et al. 2021). To integrate AI into their production processes, firms need to enhance their human capital to include AI expertise (Chen, Balasubramanian, and Forman 2021; Tambe and Hitt 2014a, 2014b). Prior literature emphasizes the significance of human capital in the spillover of IT knowledge and the necessary shift in management practices to realize IT productivity benefits (Bloom, Sadun, and Reenen 2012; Bresnahan, Brynjolfsson, and Hitt 2002). Unlike earlier information and communication technologies, AI acts as a predictive tool that aids human decision-making and requires domain-specific knowledge (Agrawal, Gans, and Goldfarb 2019; Bonelli 2022; Lou and Wu 2021; Tranchero 2023). Consequently, firms are often required to form interdisciplinary teams composed of domain experts and AI engineers, leading to potential communication frictions and challenges in teamwork. The question arises: how do firms bridge the gap between domain experts and AI engineers to encourage effective collaboration? This paper investigates the evolving role of managers, examining how firms modify managerial skill sets to accommodate the integration of AI specialists.

Prior studies investigating the effects of IT on firms' human resource management have predominantly focused on employees who are directly exposed to IT implementations, documenting shifts in skill requirements resulting from this direct exposure. Bresnahan, Brynjolfsson, and Hitt 2002 noted that the introduction of highly automated and technically complex manufacturing IT necessitates the adoption of novel work practices and a new set of skills among these workers. Similarly, Bartel, Ichniowski, and Shaw 2007 identified that the incorporation of advanced computer-based IT heightens the skill requirements of these employees, particularly in technical areas, while also fostering the adoption of innovative human resource practices. Such direct engagement with technology demands a more profound proficiency in understanding and deploying these systems, thus increasing the technical skill requirements for managers. Recent scholarship has begun to explore the organizational transformations in-

duced by IT, observing changes in the flatness of organizational structures and alterations in managers' span of control, and associating these changes with evolving managerial skill sets Dixon, Hong, and Wu 2021; Zhang 2023. However, there is limited research on the increasing significance of teamwork between IT professionals and domain experts, and its impact on the management of a firm's AI workforce and the necessary skills for managers

The deployment of AI demands substantial complementary investments in human capital and often necessitates collaboration between individuals with domain expertise and those with algorithmic knowledge (Chen, Balasubramanian, and Forman 2021; Jones 2009; Tambe and Hitt 2014a; Uzzi et al. 2013). For example, in the development of an AI-based healthcare diagnosis system, medical professionals, who possess deep clinical knowledge and patient care experience, must work closely with machine learning engineers, who apply AI algorithms to analyze complex medical data. This collaboration between professionals from distinct backgrounds enriches the project but also introduces significant communication and collaboration challenges due to their differing expertise and work cultures (Becker and Murphy 1992; Hart and Moore 2005). To mitigate these challenges, firms may strategically adjust managers' roles to bridge these gaps. In this paper, we argue firms are more likely to expect managers to be collaborators in the diverse team, emphasizing the growing importance of software and collaboration skills. Managers become crucial facilitators, translating complex technical concepts for non-specialists and fostering an environment where diverse expertise converges effectively. This indirect exposure to AI underscores the need for managerial agility in navigating the complexities of modern team dynamics, illustrating the evolving nature of managerial responsibilities in the era of AI.

There are also practical reasons to understand this issue. For businesses, adopting information technology (IT) demands significant complementary investments in business processes (Bresnahan et al. 1996; Brynjolfsson and Hitt 2000). Management practices play a vital role in innovating these processes, making it essential for companies to understand how

to execute business process innovation effectively to maximize productivity gains from IT adoption. For educators, particularly those in business schools, the relevance of the MBA degree has been challenged in recent years. Some graduates are struggling to find work months after completing their business degree [1]. Adapting to the changes brought about by the AI revolution and identifying the skills that are in demand by businesses is of paramount importance for business educators, aiming to ensure their programs meet the evolving needs of the industry.

In our empirical exploration of how the influx of AI workers (i.e. AI Adoption) impacts managerial job contents, we face several significant challenges. The first challenge is the inherent invisibility of managerial job contents. Unlike tangible outputs or measurable metrics, the nuanced tasks and responsibilities that define a manager's role are often unrecorded and deeply integrated into the organizational culture and daily operations. This obscurity hampers our ability to accurately capture and assess the evolution of these job contents over time, particularly following the integration of AI technologies. The second challenge involves the complexity of distinguishing the effects of AI adoption on changes in managerial job contents. As mentioned earlier, AI adoption can modify managers' skill requirements not only through changes in team composition but also due to direct exposure to AI and indirect organizational changes. This task is particularly challenging as these changes often occur simultaneously, making it difficult to attribute specific alterations in job content to any one factor unequivocally. A third challenge is the risk of omitted variable bias — unaccounted factors in our analysis that might affect both the decision to implement AI and the subsequent adjustment of managerial roles. For instance, the company's innovation culture or existing technological infrastructure might influence both the likelihood of AI adoption and changes in managerial tasks, yet these factors may not be fully included in our study. Additionally, we must consider the potential for reverse causality, where alterations in man-

1. Source: The M.B.A.s Who Can't Find Jobs, WSJ, https://www.wsj.com/lifestyle/careers/the-m-b-a-s-who-cant-find-jobs-669cc1fa

agerial job contents could precede, rather than result from, the adoption of AI. An example of omitted variable bias in this context could be the level of prior technological adoption within the firm. Firms with advanced technological infrastructure might be more inclined to adopt AI and simultaneously may have managers already accustomed to dynamic, tech-driven environments. If these pre-existing technological orientations are not considered, we might incorrectly attribute changes in managerial job content solely to recent AI adoption, overlooking the foundational influence of prior technological engagement.

To empirically assess the impact of AI adoption on changes in firms' managerial hiring practices, we leverage an extensive dataset of job postings. This dataset, collected and cleaned by the data team at Lightcast, encompasses detailed information on the skills required for various positions, as articulated in job postings (Deming and Kahn 2018). By analyzing the skill requirements outlined in these postings, we can precisely identify instances of AI adoption and observe how the skills demanded of managers evolve in response. We construct two dependent variables to characterize the skill requirements change of managers: the first one is an indicator which equals one if the job posting requires any kind of collaboration skills, and the second one is the ratio of software skills in the skill requirements of each job posting. Collaboration is the process of two or more people, entities or organizations working together to complete a task or achieve a goal, and collaboration skills in our setting are skills to collaborate with both IT workers and domain experts in a project or team. We proxy the inflow of AI workers using the ratio of AI-related non-manager job postings for each plant. In alignment with Babina et al. 2024, our methodology adopts a data-driven approach to define the AI-related jobs.

To ensure the validity of our causal inferences, we employ a broad set of control variables and fixed effects to address concerns related to firm size, IT investment, as well as the occupation's own exposure to AI. We also use the average AI adoption decisions of other firms within the focal firms' network as an instrumental variable (Lou and Wu 2021). The

underlying assumption for this instrumental variable is that the knowledge flows across firms that serve as a proxy for the cost of accessing AI-related knowledge and reflect the ease of accessing external AI human capital from neighboring firms. We exclude direct competitors, defined as network neighbors that are in the same industry as the focal firm. The citation neighbors also vary substantially in their industries and geographical locations and are thus less likely to be affected by common industry or region-specific shocks and competitive pressure. This strategy allows us to isolate the effect of AI adoption on managerial hiring practices from other confounding factors, drawing on established practices in the field to derive reliable causal estimates.

Our findings indicate that a ten percentage-point rise in the proportion of AI job postings leads to a 0.24 percentage-point increase in the likelihood that managerial job postings will demand collaboration skills, and a 0.21 percentage-point increase in the proportion of software skill requirements. These outcomes are noteworthy both statistically and economically, considering that merely 4.5 percent of managerial job advertisements currently specify collaboration skills, and the average proportion of software skills required in managerial positions stands at 5.9 percent. Additionally, the robustness of these results has been confirmed through various fixed effects analyses and instrumental variable estimation.

To further elucidate the mechanisms behind the impact of AI adoption on managerial job contents, we conduct a series of tests. First, utilizing data from O*NET, we identify the occupations related to each managerial position. We assume the related workers are those who interact frequently with the focal managers and can potentially be considered as team members. We find that the effects are driven solely by the AI adoption among these related workers. Second, we collect data from O*NET regarding whether the managerial job requires work activities in developing and building teams. O*NET provides the level at which each job requires developing and building teams. We use a level greater than 60 as a threshold and show that the inflow of AI workers changes the managers' skill requirements only when the

job requires extensive team-building work. Third, we characterize the different ways firms acquire AI talents: firms may acquire AI talents with domain expertise or hire AI talents to work alongside domain experts. We proxy this by calculating the ratio of AI workers in related IT occupations versus the ratio in related non-IT occupations. We demonstrate that firms are more likely to require collaboration and software skills when they hire AI workers in IT occupations, as opposed to hiring AI workers with domain expertise. Lastly, we consider the influence of corporate culture by interacting a measure of collaborative and innovative culture with the AI adoption variable. A firm's collaborative ethos may increase the necessity for managers to acquire software skills to bridge communication and collaboration gaps, yet may not increase the requirement for collaboration skills if such skills have already been embedded in the organization's culture.

We also address concerns that our findings might be influenced by managers' direct exposure to AI and alterations within the organizational structure. To this end, we integrate job posting data with online review data to determine the existing hierarchy levels within organizations and approximate the managers' span of control by calculating the ratio of employees to managers. We exclude firms experiencing significant changes in organizational hierarchy and in managers' span of control from our analysis, and find that our results still hold. Furthermore, to address the issue of managers' own direct exposure to AI, we incorporate the rate of AI adoption among managers within each firm into our model and omit IT managers from the analysis. The findings remain consistent under this specification.

This paper contributes to the literature on the impact of artificial intelligence (AI) on labor markets by elucidating how firms adopt AI to innovate their business processes. While existing studies have extensively explored the labor reallocation implications of automation and AI technologies, often challenging the notion that these technologies merely displace workers (Acemoglu et al. 2022; Acemoglu and Restrepo 2019, 2020; Agrawal, Gans, and Goldfarb 2019; Babina et al. 2022; Lebovitz, Lifshitz-Assaf, and Levina 2022; Raisch and

Krakowski 2021), our research builds upon and diverges from this narrative. Earlier literature emphasized the phenomenon of "skill-biased" technological change, reshaping job roles and altering workforce skill requirements (Bartel, Ichniowski, and Shaw 2007; Bresnahan, Brynjolfsson, and Hitt 2002). Notably, a study by Tambe delves into the emergence of algorithmically proficient individuals. Our work, however, narrows the focus to a specific occupational group — managers — and investigates a less-explored way, the team composition, that AI adoption can transform the skill composition of jobs, distinguishing our analysis from prior investigations.

Furthermore, our paper navigates the complexities faced by firms in leveraging AI to enhance their operations. While the significance of domain expertise in maximizing AI's potential as a predictive tool in decision-making is well recognized (Babina et al. 2024; Wu, Hitt, and Lou 2020; Wu, Lou, and Hitt 2019), firms encounter strategic decisions regarding the recruitment of individuals possessing both domain and algorithmic knowledge versus the formation of diverse knowledge teams. We spotlight the managerial adjustments required to address potential frictions arising from this approach, especially when bilingual workers are scarce and specialization prevails. To our knowledge, this is the first study to specifically examine how the recruitment of AI talent influences broader hiring practices within firms.

Lastly, we extend the conversation on the evolving nature of collaboration within organizations to the context of AI adoption, engaging with recent discussions on the shift in managerial roles from supervisory functions to collaborative leadership (Zhang 2023). The increasing demand for specialization and effective teamwork (Chen 2021; Jaravel, Petkova, and Bell 2018; Jin et al. 2019; Uzzi et al. 2013; Wuchty, Jones, and Uzzi 2007), driven by the expanding "burden of knowledge" (Jones 2009), necessitates a reevaluation of managerial responsibilities. Our research underscores the critical need for managers to adapt to these changing dynamics in the era of AI, thereby contributing a new dimension to the understanding of how AI integration reshapes managerial roles and organizational structures.

1 Theory and Hypothesis

1.1 AI and Domain Expertise

Artificial intelligence is increasingly utilized in production and is regarded as a new generation of general-purpose technology (Goldfarb, Taska, and Teodoridis 2023; Zolas et al. 2021). The past decade has witnessed a significant technological shift towards AI, characterized by substantial developments in artificial intelligence technologies and their widespread commercial applications (Furman and Seamans 2019). As a predictive technology, AI enables firms to learn more effectively and swiftly from vast quantities of data, potentially enhancing business decision-making significantly (Agrawal, Gans, and Goldfarb 2019). In this capacity, AI serves as a general-purpose technology that fosters growth through increased productivity and product innovation across various sectors. There is growing evidence that AI can accelerate the innovation process and boost productivity, akin to the impact of earlier generations of information technology (Babina et al. 2022).

However, unlike previous generations of general-purpose technology, AI primarily functions as a prediction tool (Agrawal, Gans, and Goldfarb 2019). Prediction involves utilizing available information to infer data that is currently unknown. For example, one might use historical weather data to forecast tomorrow's conditions or apply past image classifications to determine the labels for a new image. Essentially, this is the core of what machine learning accomplishes. It is important to note that machine learning does not establish causal relationships and should be applied cautiously due to model uncertainty and data limitations. Naturally, improved predictions lead to enhanced and more sophisticated decision-making – especially in the case of signal-contingent decisions, which alter based on the received predictions. However, algorithms based on data can exhibit significant bias if the training data are flawed (Choudhury, Starr, and Agarwal 2020; Cowgill and Tucker 2019; Fu, Huang, and Singh 2021; Van Binsbergen, Han, and Lopez-Lira 2023). For instance, a machine learning-based

hiring algorithm employed by Amazon was revealed to exhibit gender bias in 2018.

Additionally, interpreting data and understanding the underlying mechanisms of complex processes necessitate a profound knowledge of the specific domain (Tranchero 2023). For example, machine learning algorithms can be employed to sift through thousands of potential gene points to identify likely candidates for drug development. Yet, advancing these candidates to clinical trial phases demands a comprehensive understanding of the intricate interactions among these targets, a knowledge deeply rooted in the pharmaceutical domain. This necessity highlights how domain expertise is essential not only in interpreting machine-generated predictions but also in guiding the subsequent practical steps, ensuring that the transition from theoretical prediction to real-world application is both accurate and effective.

Previous research indicates that domain expertise, which refers to in-depth knowledge within a specific field, is crucial when implementing predictive technologies in production. Bonelli 2022 demonstrates that venture capitalists (VCs) can minimize failures by employing data-driven approaches to invest in startups operating in sectors with which they are already familiar. Tranchero 2023 illustrates that data-driven predictions enhance the competitive edge of firms possessing domain-specific knowledge. In the context of innovation, where outcomes are unevenly distributed and not all hypotheses can be pursued, domain expertise is invaluable in interpreting predictions and minimizing the risk of false positives. Lou and Wu 2021 find AI could potentially reduce the complexities and costs in drug discovery and the effect is particularly pronounced for developing new drugs whose mechanism of impact on a disease is known. Thus, to fully unlock the potential of artificial intelligence, the integration of domain expertise is both necessary and unavoidable.

1.2 IT Human Capital, Specialization, and Teamwork

Firm usually acquire IT-specific knowledge by hiring IT workers (Chen, Balasubramanian, and Forman 2021; Tambe and Hitt 2014a, 2014b). The implementation of new IT-related

innovations is a complex process. As with some scientific knowledge, the technical know-how required to implement new IT innovations is primarily embodied within the IT workforce, gained through hands-on experience in other firms. For instance, Tambe and Hitt 2014a find firms gain significant productivity advantages by recruiting IT personnel from firms that have previously invested heavily in IT. Additionally, recent layoffs in the technology sector have been viewed as an opportunity for firms outside the IT industry to attract AI talents. [2].

However, as previously discussed, firms need to not only acquire AI human capital but also effectively integrate this talent with domain-specific expertise. To achieve this synthesis, companies typically have two strategies: hiring individuals who possess both AI knowledge and domain expertise or recruiting specialists in each area and then organizing them into cohesive teams. While the first approach significantly reduces coordination costs, the necessity for team assembly remains critical for several reasons. Firstly, the supply of AI professionals is limited, and those with both AI expertise and domain knowledge are even rarer, as highlighted by (Benzell and Brynjolfsson 2019). This scarcity makes it challenging for firms to find individuals who can have both advanced technology skill and specialized industry knowledge. Secondly, the "burden of knowledge", a term referring to the increasing depth of expertise required to push the boundaries of a field, suggests a growing reliance on teamwork in production processes (Jones 2009; Uzzi et al. 2013). The intricacy of algorithms combined with the specific requirements of a firm's operational domain means that accumulating comprehensive expertise within a single individual is increasingly difficult. Consequently, constructing multidisciplinary teams becomes not just beneficial but essential.

In fact, teamwork has increasingly become a predominant way in the production process, and is viewed as creative combination. Research shows that high-impact work combines prior knowledge in distinctive ways, and teams are more likely to produce these distinctive creative

2. Source: Still hiring: Big Tech layoffs give other sectors an opening, AP News, https://apnews.com/article/big-tech-workers-layoffs-government-jobs-b0185388732b0aa4a92d26f4f24eba5d

combinations (Chen 2021; Jaravel, Petkova, and Bell 2018; Jones 2009; Uzzi et al. 2013). Some empirical papers has highlighted the role of automation technology in changing the composition of teams. Teodoridis 2018 finds great reductions in technology costs substitute for ex-ante optimal involvement of area specialists and facilitate involvement of outside area specialists through collaboration with researchers with broader knowledge.

1.3 Managers as A Bridge in The Team

The teamwork involved AI worker and domain experts introduces additional costs, specifically "coordination costs" for specialized workers, as theorized by Becker and Murphy 1992. In our context, these costs manifest in several ways. Firstly, when a project requires expertise from diverse backgrounds, communication among team members can become challenging (Smith et al. 1994). For instance, an AI worker might lack the comprehensive knowledge necessary to fully grasp the intricacies of drug discovery, while domain experts might struggle to understand the nuances of fine-tuning parameters in a large language model. Communication costs are often cited as a significant barrier to effective collaboration (Agarwal, Croson, and Mahoney 2010; Catalini, Fons-Rosen, and Gaulé 2020; Reuer and Lahiri 2014), with homophily, the tendency for individuals to associate and bond with similar others, identified as a potential strategy to reduce these costs. The literature suggests that people are more inclined to work with others who share similar backgrounds, a phenomenon often referred to as "birds of a feather" (Ertug et al. 2022; Ertug et al. 2018; Golub and Jackson 2012; McPherson, Smith-Lovin, and Cook 2001). Consequently, the introduction of IT workers can increase the diversity of a team in terms of knowledge and background, thereby exacerbating the challenges associated with communication.

Second, AI workers and domain experts may have divergent professional cultures and values. The recent advancements in algorithms are significantly reliant on open-source software, leading IT engineers to embrace open-source projects as a means to acquire knowledge

and contribute back to the community (Chen, Forman, and Kummer 2021; Haefliger, Von Krogh, and Spaeth 2008; Huang et al. 2022; Lerner, Pathak, and Tirole 2006; Von Krogh et al. 2012). This approach not only fosters a culture of collaboration and knowledge sharing but also aligns with the ethos of continuous improvement and transparency prevalent in the tech industry. In contrast, other industries, particularly those heavily reliant on proprietary knowledge, prioritize intellectual property, emphasizing business secrets and patents to maintain competitive advantages (Anton and Yao 2004; Graham and Hegde 2015). For example, in the pharmaceutical industry, the protection of drug formulas and research findings is paramount to securing market position and investment returns. Similarly, in manufacturing, unique production methods or materials may be guarded as trade secrets to prevent imitation by competitors. This professional discrepancy can lead to conflicts between AI workers and domain experts. IT professionals may advocate for open collaboration and the free exchange of ideas, viewing these practices as essential for innovation and progress. On the other hand, domain experts from more traditional or proprietary sectors might resist this openness, fearing the potential risks to intellectual property and commercial interests.

To foster collaboration and teamwork in AI era, firms need to make complementary investment (Bresnahan et al. 1996), one change that this paper focus is firms' expectation on managers. A manager is a person responsible for overseeing and motivating employees and for directing the progress of an organization (Mintzberg 2013). The discussion of managers' role traces back to Max Weber's era of bureaucracy, where, during the industrial age, the manager's role was primarily authoritative, centered around supervision within a hierarchical system. However, recent decades have witnessed a transformation in managerial functions. Kanter 1989 and Zhang 2023, for example, notes that managerial responsibilities are experiencing "enormous and rapid change," a trend likely driven by technological advancements and increased competitive pressures.

Accordingly, firms may adapt managers' skill sets in various ways to meet these new

challenges. Firstly, to enhance communication between specialists from diverse fields, firms might encourage managers to develop collaboration skills, moving beyond the traditional view of managers as mere supervisors within a hierarchical framework. Secondly, there is an increasing expectation for managers to gain technical competencies, particularly in software, to bridge the gap between the technical intricacies of algorithms and the operational knowledge of domain experts. This shift not only facilitates better communication but also ensures that managers can translate complex technical details into understandable terms for all team members, thereby fostering a more integrated and efficient working environment.

Two papers are notably pertinent to our research. Zhang 2023 observes that managerial role expectations have rapidly evolved across various sectors, shifting from primarily supervisory responsibilities to a focus on collaboration. This shift is attributed to technological advancements and increased organizational flatness. Dixon, Hong, and Wu 2021 demonstrates that the integration of robots within the workforce correlates with an expanded span of control for supervisors who remain in the organization. Furthermore, robots contribute to reduced variability in production processes, thereby lessening the managerial burden of monitoring worker activities to maintain production quality.

Our study, however, investigates a distinct context from the scenarios presented in the aforementioned papers. Unlike robots, which primarily serve to replace existing workers, our research concentrates on the influx of AI workers, highlighting a unique dynamic distinct from robotic automation. These AI workers necessitate a higher degree of collaboration and teamwork, diverging significantly from the implications of robot integration. Furthermore, while acknowledging the impact of organizational flattening, as driven by IT or other technological advancements, on changing managerial skill requirements, our paper introduces an additional perspective. We delve into the specific demand for integrating AI knowledge with domain expertise, a necessity that becomes particularly prominent in the AI era. This represents a novel channel through which AI influences managerial roles, underscoring our unique

contribution to the existing literature on technology's impact on management. Therefore, we reach our first hypothesis:

Hypothesis 1: *Firms are more likely to require collaboration and software skills when they have a large inflow of AI workers.*

One challenge in proving that skill changes are due to the evolving team composition and increased coordination costs is the difficulty in observing the specific teams with which managers collaborate. To address this issue, we propose several hypothesis tests. First, we proxy the teams that managers work with by utilizing O*NET data, which identifies occupations related to each managerial position. We expect that the manager skill requirements change are only driven by the inflow of AI workers in related occupations. For example, the inflow of AI workers in sales team correlates with an increase in collaboration and software skills for sales managers, but does not affect the skill modifications of human resource managers.

Second, managers differ in their work activities. Some managers are heavily involved in team development and building, while others primarily focus on supervising employees and maintaining connections with various internal and external departments. Although the interconnected roles in different departments could potentially impact managers' needs for collaboration and software skills through diffusion, this influence is likely less immediate compared to the direct necessity for enhancing teamwork. To tackle this disparity, we examine the specific activities of managers to determine whether their main tasks involve team development and management.

Third, as previously outlined, firms adopt two distinct approaches to integrating AI expertise: recruiting individuals endowed with both algorithmic and domain-specific knowledge, or forming a team that necessitates a shift in managerial skills. We distinguish these recruitment strategies by assessing whether the AI professionals hired are predominantly IT engineers or distributed among various other roles. For instance, if a company manages to hire an electrical engineer proficient in deep learning, the imperative to modify managerial

skills is less critical. Therefore, we reach our second hypotheses.

Hypothesis 2.1: *Firms are more likely to require collaboration and software skills when they have a large inflow of AI workers in their related occupations.*

Hypothesis 2.2: *Firms are more likely to require collaboration and software skills when managers' main work activities are working and building teams.*

Hypothesis 2.3: *Firms are more likely to require collaboration and software skills when they have a large inflow of AI workers in their related IT occupations.*

While the change of managerial skill requirements may mitigate the collaborative frictions introduced by the influx of AI workers, the impact of such changes can be moderated by additional institutional factors. One significant element is corporate culture, defined as "a system of shared values that delineate priorities and appropriate behaviors for organizational members." (O'Reilly 1989) Literature identifies five key dimensions of corporate culture: innovation, integrity, quality, respect, and teamwork (Guiso, Sapienza, and Zingales 2015; Li et al. 2021), with innovation and teamwork being particularly pertinent to our research. A good corporate culture fosters teamwork, potentially reducing the necessity for managers to obtain collaboration skills, yet it might amplify the need for them to develop software capabilities as managers are increasingly viewed as team collaborators. This leads to the formulation of our third hypothesis.

Hypothesis 3: *Firms are less likely to require collaboration but more likely to require software skills when they have good teamwork and innovation culture.*

Despite significant effort to support the theory that changes in managerial skills are necessitated by the integration of AI specialists and domain experts, doubts remain that such shifts could also stem from organizational transformations, such as increased organizational flatness and a reduced managerial span of control. Illustrative of this is the growing adoption of the matrix organizational structure, characterized by dual reporting lines, typically one functional and one project- or product-based. This framework promotes interdisciplinary

cooperation but also compels managers to act as connectors and operate across diverse domains. Information technology might spur organizational transformations, and observed changes in managerial skills could reflect adaptations to AI-induced organizational shifts rather than changes within teams. Acknowledging this potential, we hypothesize that the observed trends will persist even when accounting for organizational changes, leading to our fourth hypothesis.

Hypothesis 4: *Firms are more likely to require collaboration and software skills when they have a large inflow of AI workers without changing the organization structure.*

2 Data and Empirical Strategy

2.1 Data

Job Posting Database. Our primary dataset is the Lightcast (formerly known as Burning Glass) Job Posting Database. Lightcast methodically reviews over 40,000 online job boards and company websites, compiling job postings data, which it then organizes into a structured, machine-readable format for labor market analysis. The company employs a sophisticated deduplication algorithm to prevent the recounting of identical job postings appearing on multiple job boards. The job postings data includes details such as the employer's name, job title, geographical location of the position, skills and educational requirements sought from candidates, salary offered, and other relevant attributes for the application process, covering the period from 2010 to 2022. We utilize this dataset to assess the requirements for collaboration or software skills in job postings and to measure the influx of AI workers (i.e. AI adoption).

The job postings data provides several significant advantages: First, the dataset offers extensive coverage and detailed insights into individual job postings, capturing the near entirety of online job advertisements and about 60–70% of all job vacancies in the U.S.,

whether posted online or offline. Hershbein and Kahn 2018 provides a comprehensive review of the job postings data, confirming its consistency and representativeness across different occupations over time. This extensive coverage allows us to analyze AI adoption and firms' skill requirements accurately. Second, Lightcast standardizes the job postings data, including a detailed taxonomy of skills in the database and linking each job posting to a Bureau of Labor Statistics' O*NET code, while each employer in the postings is categorized under a North American Industry Classification System (NAICS) industry. This standardization facilitates the construction of variables regarding the types of skills required and valued by firms.

In our analysis, we focus on job postings with non-missing employer names and at least one required skill listed. Approximately 65% of the job postings include employer information, and more than 90% of job postings specify at least one required skill. We then match the employer firms from these job postings with Compustat firms that have patent information, a crucial step for calculating firm-level AI adoption and merging with other firm-level control variables, such as total assets and market value. We perform a fuzzy matching process after standardizing company names using an algorithm from the NBER patent project. For entries that do not precisely match by company name, we manually review the top ten potential fuzzy matches, considering aspects such as the firm's name, industry, and location. Ultimately, our dataset includes 2,700 firms and encompasses 46 million job postings, including around 4 million specific to managerial positions.

Additional Data Sources. To categorize manager job postings and assess the related jobs for each managerial occupation, we associate the O*NET codes present in the job posting data with the Occupational Information Network (O*NET) content model, which is provided by the Bureau of Labor Statistics. The O*NET database, extensively employed in scholarly research (Autor, Levy, and Murnane 2003), is administered by the government and compiled through surveys of occupational experts. It offers comprehensive data on employment, wages,

and the work attributes of U.S. jobs at the occupational level. The O*NET taxonomy outlines work attributes, including the knowledge needed for various roles. In parts of our analysis, we explore the moderating impacts of corporate culture. For this, we acquire corporate culture information from the study by Li et al. 2021. To construct the instrumental variable for our research, we depend on the firm's patent citation network, with the data derived from the USPTO's PatentView database.

2.2 Variables

Dependent Variables. We focus on two key facets reflecting the evolving expectations of managerial skills: collaboration and software skills. Lightcast has assembled a dedicated full-time ontology team tasked with identifying an extensive array of skills—over 30,000 in total—encompassing both technical abilities, such as proficiency in Python, and cognitive and social competencies, like analytical thinking and collaboration. To pinpoint the required skills for each position, the Lightcast team devised a comprehensive set of rule-based linguistic classifiers, which include thousands of rules and keywords, augmented by a variety of contextual and negation rules.

Utilizing these classified skills, we delineate the skill requirements covered in each job posting. More precisely, we create two dependent variables: the first is a binary indicator set to one if the job posting specifies a need for collaboration skills, including collaboration, virtual collaboration, project collaboration, and social collaboration (All the skills are listed in Table A.1); the second quantifies the proportion of software skills demanded in the posting. Lightcast categorizes collaboration as a distinct skill set and enumerates the requisite software skills for each position. While it is conceivable that other skills could synonymously represent collaboration, we conducted a manual review of all listed skills and identified a few potentially related ones, such as teamwork, coordination, and cooperation. There skills may not be identical to collaboration skills, for example, teamwork skills are the collaborative

effort of a group to achieve a common goal or to complete a task in an effective and efficient way, and are often involves a defined team structure with clear roles and responsibilities for each team member, while collaboration is more about the process and can be more fluid in terms of structure and roles. Nevertheless, inclusion of these skills does not materially alter the analysis's outcome, we opted not to incorporate them into our study. Additionally, Lightcast organizes software skills into a distinct cluster, and we directly apply this classification in our evaluation.

Independent Variables. Our primary independent variable examines the influx of AI workers, quantified by the ratio of non-managerial AI-related job postings for each establishment. To classify a job posting as AI-related, we utilize a data-driven method as proposed by Babina et al. 2024, focusing on the AI-relatedness of each skill presented in the postings. This AI-relatedness is determined based on the skills' empirical co-occurrence with key AI competencies, namely, Artificial Intelligence (AI), Machine Learning (ML), Natural Language Processing (NLP), and Computer Vision (CV)—within the lists of skills required across various job postings. We compute an AI-relatedness score for each job posting by averaging these co-occurrence-based scores across all required skills. A job posting is deemed AI-related if its AI-relatedness score exceeds the threshold of 0.1. We then define the AI adoption measure for a plant as the fraction of its job postings in a given year that are AI-related.

We assume that the proportion of AI-related job postings is a valid indicator of the influx of AI workers. This premise relies on the supposition that the volume of job postings is indicative of actual employment numbers across different professions and companies. Although direct confirmation using actual employment figures is not available, previous studies suggest that job posting data are representative across different regions and job categories and correlate well with the actual employment figures (Hershbein and Kahn 2018). Furthermore, patterns observed in job-posting-derived AI adoption metrics are consistent with

those derived from actual workforce data, as noted by (Babina et al. 2024). Consequently, we consider the proportion of AI-related job postings as a dependable proxy for the influx of AI workers. For robustness, we also examine alternative metrics, such as the logarithmic count of AI-related job postings and keyword-based AI indices outlined by Acemoglu et al. 2022.

In additional analyses, we split the AI adoption indicator by separating AI-related job postings into those associated with the manager occupation and those that are not. Utilizing the Lightcast dataset, we connect each managerial position with its related non-managerial occupations, as categorized by O*NET, typically ranging from five to twenty related roles. For example, a sales manager is related to non-managerial occupations, such as advertising sales agents, market research analysts and sales representatives of services. We calculated the AI adoption ratio of all the related occupations and all other unrelated occupations. Moreover, to proxy different ways of hiring AI workers, we further split the related jobs into related IT jobs and related other jobs, and calculate the AI adoption rate for each category. This approach allows us to examine the source of the variation and shed light on our mechanism tests.

Other Variables. First, to explore the moderating effects of corporate culture, specifically in the realms of teamwork and innovation, we employ two dummy variables. These indicators are set to one for companies with teamwork or innovation scores above the median, respectively. The dummy variable allows us to better explain the effects of the corporate culture as the meaningless cultural scores is hard to interpret in regression models.

Second, we also exclude the influence of changes in firms' organizational structure within our analysis, we introduce two variables as proxies for these structural shifts. Initially, we construct the hierarchy levels of the firm using the methodology outlined by Lee 2022. The number of hierarchy level is computed by first categorizing each employee's job title into one of 12 levels (i.e., "Owner," "President," "VP," "CEO," "C-Suite," "Head," "Director," "Manager," "Producer," "Lead," "Supervisor," and "Other") and then counting the number

of unique levels. To mitigate biases associated with hiring practices, this dataset is augmented with job titles from online reviews. These levels, rooted in qualitative analysis and confirmed through expert interviews, are detailed further in Lee 2022. However, we note that the data on hierarchy levels may contain noise due to irregular hiring patterns or infrequent employee feedback. To address this, we create a dummy variable that identifies sustained organizational changes, specifically if a firm shows a reduction in two or more hierarchy levels over a span of three years or more. Furthermore, we examine the managers' span of control, guided by the approach proposed by Dixon, Hong, and Wu 2021, by calculating the average number of employees per manager. In alignment with the concept of organizational flatness, we formulate another indicator variable. This variable becomes one if a significant alteration, exceeding a standard deviation, occurs in the span of control within the firm over a period exceeding three years, thereby providing a quantitative measure to evaluate substantial shifts in managerial dynamics.

Third, we include controls at job posting, plant, and firm level. At job posting level, we include several binary variables indicating whether the job is a full-time job, requires MBA degree, requires graduate degree, and a continuous variable, the minimum years of work experience, and the number of all required skills. These variables allows us to control the heterogeneity and confounders that affect skill requirements from the job postings. At plant level, we add the the number of all job postings, and number of all IT job postings. The first one proxy the size of the plant, and the second one proxy the IT investment of the plant. The size and IT investment can be correlated with the AI adoption rate of firms and skill requirements of the manager jobs. For example, an IT intensive firm may be more likely to adopt AI quickly as it has the digital infrastructure and require more software skills. At firm level, we include the number of employees, the total assets, the total intangible assets, property, plant, and equipment, and market value as control variables.

Table 1 presents descriptive statistics and correlation matrix for our main variables. There

are 4,229,590 job postings in our database, and one job posting requires 20 (2.93 after taking the log) skills on average. However, less than 5 percent job postings require collaboration skill and the mean of the ratio of software skills is around 5.8 percent.

2.3 Empirical Strategy

Our primary specification examines changes in manager' skill requirements in response to firms' influx of AI workers between 2010 and 2022. Our baseline estimation model takes the following form:

$$Y_i = \alpha + \beta AIAdoption_{j,m,t} + \gamma_1 X_{i,t} + \gamma_2 Z_{j,t} + \gamma_3 T_{j,m,t} + \rho_j + \pi_m + \phi_o + \lambda_n + \kappa_t + \eta_h \epsilon_{i,t} \quad (1)$$

Where Y_i is the measure of outcome, and we have two outcome variables. One is a binary variable indicating whether the job posting i posted in year t required collaboration skill, the other one is the ratio of software skills expected in the job posting i posted in year t. $AIAdoption_{j,m,t}$ a continuous variable ranging from 0 to 1, characterizing the ratio of AI-related job postings in non-manager jobs for firm j in Metropolitan Statistical Area (MSA) m in year t. We define a plant as a firm j-MSA m combination. The definition and calculation of AI-related jobs are discussed in previous section. $X_{i,t}$ is a vector of control variables at job posting level that may directly affect the job requirements. $Z_{j,t}$ and $T_{j,m,t}$ are control variables at firm or plant level, respectively. These control variables proxy the size, previous IT investment, and the fixed capital of the firm and the plant that may affect both AI adoption decision and managers' skill requirements in the same time.

We incorporate month fixed effects, denoted as η_h, to address fluctuations in skill requirements linked to hiring seasons, alongside year fixed effects, κ_t, to mitigate the impact of temporal variables. Industry-specific variations in skill demands are accounted for through

industry fixed effects, λ_n, determined by the 6-digit NAICS code of the employing firm. Additionally, we integrate Metropolitan Statistical Area (MSA) fixed effects, π_m, as the location of a job is not only associated with the AI labor supply specific to the geographical region but also serves as a critical factor influencing the skill expectations of firms. Firm-specific preferences, age, and other time-invariant attributes are controlled by including firm fixed effects, ρ_j. Furthermore, occupation fixed effects, ϕ_o, are applied using O*NET job classifications as a proxy. The inclusion of occupation fixed effects allows us to conduct a comparison of two jobs with identical job codes, therefore, the effects we estimate is within same jobs instead of characterizing the differences or transitions across jobs. In a robustness check, we employ plant-level (firms $\times$ MSA) fixed effects, finding similar results. However, to avoid computational burden in our estimation, we continue to utilize the original specification across all subsequent analyses.

We are primarily interested in β, which denotes the average skill requirements difference between plants with high AI adoption rate and plants with low AI adoption rate, after controlling for other factors. More specifically, if β is positive and significant, it suggests that more influx of AI workers (i.e. higher AI adoption rate) will prompts a shift in employer expectations towards to require collaboration skill and more software skills.

Our identification assumption is that there are no firm-level or local-level unobservables that are correlated with the adoption of AI in non-manager occupations and the skill changes of managers. This assumption, however, may be compromised by various potential violations. First, there are some unobserved variables that could concurrently influence both AI adoption decision and the shift in managerial skill needs. For instance, a firm's decision to implement a digital retailing platform may not only necessitate an influx of AI professionals to address technical challenges but also alter the skill set required of sales managers who interact with the new platform. Similarly, high-performing firms possessing surplus resources might opt to invest in AI technologies while also adopting superior management practices. Second, there is

possibility for reverse causality, where alterations in managerial job contents could precede, rather than result from, the adoption of AI.

We employ several strategies to mitigate potential biases arising from violations of our identification assumptions. First, in our estimation model, we incorporate an extensive array of control variables and fixed effects designed to account for possible confounding factors, including firm size and IT investments. Second, as part of our mechanism analysis, we specifically exclude IT managers from our dataset and control for the AI adoption rate among managers at each plant. This method allows us to directly address the impact of managers' exposure to AI, particularly through the implementation of digital platforms, thereby tackling the concern that observed changes in skill requirements might be primarily due to direct AI involvement.

Third, we leverage the average AI adoption rates of other firms within the focal firm's network as an instrumental variable, following the methodology used by Lou and Wu 2021. To construct this, we gather patent citation data for each firm in our dataset, creating a network where firms are nodes and links cumulative patent citations over the past three years. For instance, if Firm A's patents have cited Firm B's patents five times within this time frame, we establish a directed link from A to B with a weight of five. Notably, this relationship is unidirectional: if Firm B does not cite Firm A, then there is no reciprocal link, indicating no knowledge flow from B to A. We then calculate the weighted AI adoption rates of neighboring firms using the calculated weights. The underlying assumption of using this instrumental variable is that knowledge transfer among firms acts as a proxy for the costs associated with accessing AI technology and reflects the ease of acquiring external AI expertise from neighboring entities. We exclude direct competitors from this analysis to avoid bias, defining competitors as those in the same industry and therefore likely subject to similar market forces and conditions. Additionally, since citation neighbors often belong to diverse industries and regions, they are less prone to common industry or geographical shocks and competitive

dynamics. This approach aims to isolate the influence of AI adoption on managerial hiring practices from other confounding variables, employing recognized methodologies to obtain robust causal inferences.

We investigate the variations in the impact of AI adoption on managerial skill requirements across different factors such as establishment size, proximity to AI hubs, and the firm's industry. These additional analyses provide additional confidence in the causal interpretation of our results, especially if they align with the theoretical framework established earlier. Specifically, a consistent pattern of results across these dimensions would suggest that any unobserved heterogeneity influencing our findings behaves in a manner that aligns with our theoretical expectations regarding the interactions between establishment size, industry, and geographic location in relation to AI adoption.

In some of our mechanism tests, we split the overall AI adoption rate into distinct segments based on their relevance to the manager occupations. Specifically, for each managerial occupation, for example sales managers, instead of a singular, aggregate AI adoption rate, we now differentiate between two distinct types: the AI adoption rate for jobs that are directly related to each specific manager occupation and the AI adoption rate for jobs that are unrelated. In one test, we further split the AI adoption rate for jobs that are directly related to each specific manager occupation into AI adoption rate of IT relevant jobs and AI adoption rate of non-IT relevant jobs. This approach allows us to examine the source of the variation and shed light on our mechanism tests. The estimation equations are as follows:

$$\begin{aligned} Y_i = \alpha &+ \beta_1 AIAdoptionRelated_{j,m,o,t} + \beta_2 AIAdoptionNonRelated_{j,m,o,t} \\ &+ \gamma_1 X_{i,t} + \gamma_2 Z_{j,t} + \gamma_3 T_{j,m,t} + \rho_j + \pi_m + \phi_o + \lambda_n + \kappa_t + \eta_h \epsilon_{i,t} \end{aligned} \tag{2}$$

$$\begin{aligned} Y_i = \alpha &+ \beta_{11} AIAdoptionITRelated_{j,m,o,t} + \beta_{10} AIAdoptionITRelated_{j,m,o,t} \\ &+ \beta_2 AIAdoptionNonRelated_{j,m,o,t} \\ &+ \gamma_1 X_{i,t} + \gamma_2 Z_{j,t} + \gamma_3 T_{j,m,t} + \rho_j + \pi_m + \phi_o + \lambda_n + \kappa_t + \eta_h \epsilon_{i,t} \end{aligned} \tag{3}$$

3 Results

In this section, We first investigate whether higher AI adoption rate are associated with a higher demand for collaboration and software skills. We then investigate differences in our results based upon the firm size, the characteristics of the location in which the establishment is situated, and the industry of the firm. We then explore the mechanism and partial out other potential explanations. We finally examine robustness with respect to sample and specification.

3.1 Baseline Results

Table 2 presents the fixed effects regression estimates of the impacts of AI adoption on managers' skill requirements. Columns (1) to (4) display the impact of AI adoption on collaboration skill requirements, measured by an indicator variable which equals to one if the any collaboration skills are required in that job posting, and Columns (5) to (8) use the ratio of software skills in each job posting to capture the software skill requirements. Columns (1) to (3) and columns (5) to (7) include company, msa, industry, occupation, year and month fixed effects to control time-invariant characteristics. Columns (4) and (8) replace the company and MSA fixed effects to plant (firm $\times$ MSA) fixed effects. All models include control variables at job posting level, plant level, and firm level. All the models are estimated using linear model.

Columns (1) to (4) show the firms' AI adoption increase collaboration requirements significantly, and this finding is robust across different model specifications. More specifically, ten percentage-points increase in AI adoption rate is related to 0.27 percentage-points increase in the probability that collaboration skill is included in the plants' job postings. This effect is of economic significance and represents 5 percent increase, considering only 4.5 percent job postings include collaboration skill. Columns (3) to (4) show the firms' AI adoption increase the ratio of software skills requirements, with 0.27 percentage-points increase in software

skills for each additional 10 percentage points increase in AI adoption rate. There results support our hypothesis 1 and are consistent with existing literature that the implementation of IT requires complementary organizational change, including skill requirements.

Table 3 examines the heterogeneous effects of firm entry across different types of firms. Columns (1) and (2) display the impact of AI adoption on collaboration skill requirements, and Column (3) and (4) use the ratio of software skills in each job posting as dependent variable. We estimate separate regressions for the two groups to allow for unrestricted effects of covariates in differently firms.

Panel A of Table 3 shows that split-sample results that estimate different AI adoption coefficients for establishments near AI-strong university (i.e. in the same MSA) versus establishments that are far-away from any AI-strong university (i.e. not in the same MSA). AI-strong universities are universities whose number of AI researchers is at the top of the distribution. Columns (1) and (2) show that the AI adoption has effect on collaboration skill requirements for both firms near AI-strong universities and those who are not, yet the effects on the skill requirements of near AI-strong university firms are slightly larger. The results on software skills are similar.

In panel B, we compare the effects across firms of different scales. Column (1) and (3) show that the AI adoption has a 3.3 percentage points and 3.9 percentage points effect on collaboration skill and ratio of software skill requirements, respectively, for plants that are belong to superstar firms. Column (2) and (4) display that AI adoption has positive but noisy effects in skill requirements for plants that are not superstar firms. Superstar firms are defined as top 500 large Compustat firms in terms of market value. Existing literature has found that superstar firms have higher productivity, management practice, and usually accumulate more digital capital (Autor et al. 2020; Tambe et al. 2020).

We split the sample into IT firm (NAICS code = 51 or 54) and non-IT firms in panel C of Table 3. We find the AI adoption has effects on skill requirements for both IT firms

and non-IT firms, even though the effects on collaboration skill for IT firm is with much variation. This test reveals that our results are not only driven by IT firms who may produce AI tools, but driven by downstream non-IT firms who adopt and use AI in their business process.

Table 4 shows the IV estimation results. The first stage estimation is significant and with F-statistics greater than 10, which proves that this IV is not a weak IV. The 2SLS estimations on AI's effect show consistent results. One potential concern is that the coefficients of IV estimation is around 10 times larger than the OLS estimation. This may be a result of the local average treatment effects of the IV estimation, and is not a rare case. In fact, Jiang 2017 find that the magnitude of the IV estimates is, on average, nine times of that of the uninstrumented estimates even when economic insights do not suggest a downward bias of the latter.

3.2 Mechanism Tests

We establish the causal relationship between AI adoption and requirements to managers' skills in the previous section, and in this section, we perform several tests to prove that the changing expectation of managers' skills is driven by the influx of AI worker and the need of teamwork. While we don't deny the existence of other mechanisms, such as organizational structure change and direct exposure to AI, we show that the effects exist even after we take these channels into consideration.

Table 5 split the AI adoption rate across all non-managerial occupations into AI adoption rate of related jobs for each manager occupation and AI adoption rate of non-related jobs. Each manager occupation has its own related occupations in O*NET database. For example, a sales manager is related to non-managerial occupations, such as advertising sales agents, market research analysts and sales representatives of services. We assume these related non-manager occupations can serve as a proxy for the team that the managers work with. We find

only AI adoption of manager-related jobs can affect the skill requirements of corresponding manager job postings. Specifically, ten percentage points increase in AI adoption rate is related to 0.13 percentage points increase in the probability of requiring collaboration skill and 0.27 percenrage points increase in the ratio of required software skills, as suggested by columns (1) and (2) of Table 5, respectively. These results suggest the effects of AI adoption on managers' skills are not driven by firm-wide or plant-wide systematic changes, instead, the effects are more likely to be driven be exposure to the AI workers.

Table 6 further examines how the effects of AI adoption affect different managers. Managers are not homogeneous, on the contrary, managers differ a lot in their work activities. In this test, we focus on one work activity that is directly related to our theory, the teamwork. O*NET provide the level of the manager job involving much activities in building and developing teams. This measure ranging from 0 to 100, and we take the level greater than 60 as an indicator that team building is an important duty for the managers. Columns (1) and (3) presents the AI adoption rate of manager-related jobs increase the collaboration and software skills for managers who need to build and develop a team. The effects are weaker or not significant for managers who don't need to build a team, as shown in columns (2) and (4). These results are consistent with our theory that the managers need to serve as a bridge in a team when there is much influx of AI workers with different knowledge background and work profession.

Table 7 dives into the different hiring strategies of the firms. As we discussed before, firms may acquire AI talents with domain expertise or hire AI talents to work alongside domain experts. If the firm hire AI talents with domain expertise, then it may not be necessary for the managers to change their skills. However, if the firm hire AI talents to work alongside domain experts, firms are more likely to expect managers to change their skills to coordinate the team members. To test this hypothesis, we further split the AI adoption rate of the manager-related jobs into two parts, one is the AI adoption rate of the manager-related-IT

jobs and the other one is the AI adoption rate of the manager-related-non-IT jobs. Columns (1) and (3) contain all managers with at least one IT related jobs, and columns (2) and (4) exclude IT managers. We find the AI adoption effects on managers' collaboration and software skill requirements are mainly driven by AI adoption in the manager-related-IT jobs, which supports our theory.

Table 8 examines the moderating effects of corporate culture. We focus on two aspects of corporate culture, teamwork and innovation, that are relevant to team, and we code the facets of corporate culture as binary variables which equals one if the corresponding scores are greater than the median. Columns (1) and (2) show that firms with good teamwork culture and innovation culture are 3.3 and 3.1 percentage points, respectively, less likely to require collaboration skill. Since corporate culture is a form of values and norms that are shared and recognized by corporate members, it may serve as a substitute to the formal requirements. Columns (3) and (4) present that firms with good teamwork culture and innovation culture are more likely to require managers to have software skills when they adopt AI, even though the moderating effects of teamwork culture is not significant. These results indicate that the collaboration culture inherited in the firm necessitates the needs for managers to obtain these software skills.

Combined together, Tables 5 to 8 provide direct evidence that the effects of AI adoption on managers' skill requirements are driven by the needs to coordinate team members with different background and increasing communication frictions. For the left part of this section, we discuss other potential mechanisms, and show our results are robust after considering these alternative explanations.

One potential explanation of the effects of AI adoption on managers' skills is the organizational change, for example, organization flatness and span of control. The past several decades has witnessed the growing adoption of the matrix organizational structure, characterized by dual reporting lines, typically one functional and one project- or product-based.

This framework promotes interdisciplinary cooperation but also compels managers to act as connectors and operate across diverse domains. We calculate the organizational hierarchy levels and managers span of control. For Table 9, we exclude organizations with hierarchy levels decrease 2 or more for at least 3 years, and for Table 10 we exclude organizations with span of control decrease one or more standard deviation for at least 3 years.

Table 9 shows that the effects of AI adoption on managers' skills change remain nearly the same as Table 2 after we exclude the organizations with decreasing hierarchy level. Table 10 shows that the effects of AI adoption on managers' skills change still hold but become weaker compared to that in Table 2 after we exclude the organizations with much change in managers' span of control. These results don't deny the existence of organizational structure change as a channel that AI adoption drives managers' skill changes, however, we find support that our results are robust even after accounting for these changes.

Another potential explanation is the effects are driven by the direct exposure of the managers and their team members. This concern are more likely to be true for certain firms and occupations. To deal with this challenge, we include the AI adoption of managers in the firm as a control variables and exclude IT managers who are most likely to affected by this channel. Table 11 provide empirical tests to this hypothesis. Columns (1) and (2) show the effects of AI adoption on collaboration skills are nearly the same even after controlling the manager's AI adoption rate. Column (3) shows that the effects of AI adoption on software skills requirements become insignificant, however, this doesn't indicates the effects disappear. Column (4) presents the effect still holds for related jobs even though the magnitude becomes smaller.

3.3 Robustness Check

We explore the robustness of our results to changes in specification. We examine the effects of AI adoption on managers' skill requirements using other definitions of AI adoption. More

specifically, we calculate AI adoption rate using key word approach to define whether a job posting is AI-related or not. The key word list is provided by Acemoglu et al. 2022, and we define a job as AI-related if its skill set include one or more skill in the key word list. Columns (1) and (4) show the results. The effect of AI adoption on collaboration skill is consistent with our main specification, and the effect on software skills is also significant and positive. We also tried to compute the AI adoption rate of all jobs instead of just non-manager jobs. Lastly, we use the log number of all AI-related jobs as independent variable, as shown in columns (3) and (6), the effects are similar.

We also test the robustness of our dependent variable. There is possibility that some skills are similar as collaboration skill but in a different name, therefore, we manually check the skill list and pick several other skills that are close to collaboration skill. According to "Merriam-Webster" dictionary, there are three words that are synonyms of collaboration: cooperation, coordination, and teamwork. We manually check skills that are related to the three words. We find the results are robust to different definition of collaboration skills, yet there are some slight differences. For example, more jobs require teamwork and the variation is larger after we add teamwork in our measurement. The reason may be that teamwork may involve specialization in the team instead of close collaboration of team members.

We implement a falsification test. Instead of using collaboration skill, I use another set of skills, such as common skills and cross-functional skills. Cross-functional skills are skills to work cross boundaries of prior duties and often happen when there the organization becomes flatter. Common skills or social skills include collaboration and other skills such as communication and presentation, these skills may increase due to any kind of teamwork (Backus, Conlon, and Sinkinson 2021). We find the AI adoption doesn't increase the need of cross-functional skills, and decrease the need of common social skills. This proves our theory that the skill change of managers is driven by the need to bridge AI workers and domain experts within a team, instead of regular teamwork or the need to collaborate with other

teams.

3.4 Other Tests: Skills and Salary

In the last part of this section, we provide suggestive evidence to the following two questions: (1). how does the skill changes affect the salary of managers and (2). can business education and experience moderates the skills' effects on salary. Column (1) suggests that collaboration skill is positively related to the salary, while Column (4) indicates a negative association between software skills and managers' salary. Column (2) and (5) shows the moderating effects of MBA degree. Column (3) and (6) shows the moderating effects of work experience. The variation of the moderation effects are relatively large, which suggest both MBA training and the work experience cannot substitute the requirements of collaboration and software skills.

4 Discussion

In this paper, we explore how firms modify managerial skill sets to accommodate the integration of AI specialists. Prior research in IT literature has focused on how IT implementation can change skill requirements of directly-exposed workers, especially IT workers. We highlight another mechanism through which the AI adoption necessitates the teamwork and increase the coordination and communication costs. Specifically, we provide a framework for demonstrating how firms change their expectation about managers in response to the rising teamwork between AI workers and other domain experts.

We bring this framework to the data by examine two skills, collaboration and software skills. Taking advantage of the comprehensive job posting data, we document that the AI adoption will induce firms more likely to include collaboration and software skill in the job posting requirements. There effects are not merely driven by IT firms or firms that are

close to AI-strong universities, and are stronger for superstar firms which have much digital capital accumulation. Further investigation on the mechanism suggests that the effects are driven by AI adoption of manager-related jobs, especially when the related jobs are IT jobs without domain expertise. Moreover, the effects only exist for managers who need to build and develop a team and are moderated by the corporate culture of the firm.

We also deal with concerns about other potential explanations. We calculate the organizational hierarchy levels and span of control, and exclude organizations with significant changes in the organization structure in some of our analysis. The results are robust. Another test involves the direct exposure to AI by the managerial occupations, we exclude IT managers and add AI adoption rate of managers, and the results remain similar.

Our results join the discussion about how firms' complementary investment and organizational change can release the productivity effects of IT. Prior literature has highlighted the importance of organizational change and the skill change driven by IT (Bresnahan, Brynjolfsson, and Hitt 2002, e.g.). However, most of the papers focus on the direct exposure to IT hardware or software, in other words, the need to change the skills is caused by the necessity to use the IT tools in production process. Our paper is different as we highlight the need to change the skills may be a consequence of the need to coordinate IT workers and domain experts, which is especially important in AI era as AI requires not only input from the IT workers but also from the domain experts.

This paper also contributes to a growing literature about teamwork in the organization (Jones 2009, e.g.). The increasing "burden of knowledge" enables specialization and the need to form a team and collaboration. Earlier generation has highlight the "burden of team", that is, the coordination costs (Becker and Murphy 1992, e.g.). This paper join the literature by providing empirical evidence in AI setting.

This paper also has managerial and policy implications. For firms, the scarcity of AI talents makes firms hard to acquire workers with both domain expertise and AI skills. To

utilize AI into business process, firms need to form a team. For the past several years, the layoff of tech companies has been taken as a chance for other firms to acquire AI talents and adopt AI into production. However, to realize the productivity benefits of these workers, firms need to make complementary changes. We highlight one change that firms can make, the skill requirements of managers. For educators, particularly those in business schools, the relevance of the MBA degree has been challenged in recent years. Some graduates are struggling to find work months after completing their business degree. Our research indicates that the changing skill requirements for managers can possibly depreciate the management education.

Our research has limitations and suggest avenues for future research. One concern is the measurement of AI adoption and team. In an ideal case, we can measure the inflow of AI workers and detailed information about who they work with. However, due to data limitation, we can only proxy the inflow of AI workers and teams by using the job posting and O*NET data. While the data has been proved to be representative and reliable in other settings, there is possibility that the measurement error exists. Future research may think about implementing analysis in a relatively smaller sample but with more detailed data to acquire more insights on the dynamics of teams and accurate measurements.

Second, our sample is mainly focus on public Compustat firms and may over-represent large firms and firms with high productivity. For small firms, such as startups, they may show different patterns in their organization and skill changes with respect to the inflow of AI workers. Existing literature has highlighted that startup workers have different work activities and duties and less specialization, and it would be worthwhile to investigate whether and how the effects of AI adoption on startups are different from established public firms.

Lastly, while we use an instrumental variable to establish the causal relationship between AI adoption and the skill requirements of managers, there is still possibility that there are some other omitted variables that affect both instrumental variable and the skill require-

ments. We admit it's a hard question to have totally exogenous variation in AI adoption, it may be possible to propose a better instrumental variable with better data available.

Our research has taken a first step toward understanding how the combination of AI workers and domain experts can change managers' skill requirements. However, there remains many ways to build on these results. As we discussed above, there are opportunities to study detailed labor dynamics, especially the team, with detailed data as well as to study the effects of AI adoption on startups, instead of public firms. We hope our research encourages additional work in this important area.

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Tables

Table 1: Descriptive Statistics and Correlations

Var.	N	Mean	S.D.	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Collaboration Skill Required	4229590	0.0458	0.209	0.0000	1.0000	1.00														
Software Skills (Ratio)	4229590	0.0585	0.087	0.0000	1.0000	-0.01	1.00													
AI Adoption Rate	4229590	0.0396	0.060	0.0000	1.0000	0.02	0.01	1.00												
Num. of All Required Skills (Log)	4229590	2.9335	0.615	0.6931	5.9989	0.12	0.18	-0.11	1.00											
Full-Time Job	4229590	0.9527	0.212	0.0000	1.0000	0.02	0.04	0.02	0.09	1.00										
MBA Required	4229590	0.1281	0.334	0.0000	1.0000	0.06	-0.05	0.04	0.20	0.05	1.00									
Graduate Degree Required	4229590	0.0484	0.215	0.0000	1.0000	0.03	-0.03	0.01	0.06	0.02	0.13	1.00								
Minimum Work Experience	4229590	4.3808	3.902	0.0000	15.0000	0.06	0.01	-0.01	0.32	0.11	0.15	0.06	1.00							
Num. of All Jobs	4229590	1.5244	4.184	0.0100	55.7240	0.01	0.02	0.15	0.00	-0.01	0.08	0.02	0.03	1.00						
Num. of All IT Jobs	4229590	0.4506	1.293	0.0000	13.3550	0.02	0.05	0.21	0.03	0.04	0.10	0.02	0.07	0.80	1.00					
Num. of Employees (Log)	4229590	10.4576	1.937	0.0000	14.6484	-0.00	-0.03	0.15	-0.07	-0.07	0.02	-0.01	-0.04	0.30	0.27	1.00				
Assets (Log)	4229590	3.2484	1.675	0.0000	7.7243	0.04	-0.00	0.17	0.04	0.00	0.07	0.04	0.04	0.27	0.25	0.79	1.00			
Intangible Assets (Log)	4229590	2.0196	1.465	0.0000	5.7404	0.04	0.00	0.07	0.09	0.03	0.07	0.04	0.09	0.16	0.16	0.67	0.84	1.00		
Property, Plant, and Equipment (Log)	4229590	2.1897	1.479	0.0000	5.8821	0.01	-0.03	0.20	-0.02	-0.03	0.04	-0.00	-0.01	0.32	0.27	0.79	0.84	0.68	1.00	
Market Value (Log)	4229590	3.4193	1.773	0.0000	7.8359	0.06	0.01	0.23	0.06	0.02	0.10	0.06	0.06	0.33	0.32	0.74	0.87	0.77	0.78	1.00

Notes. Each observation is at job posting level. Only manager jobs (O*NET code: 11) are include in the analysis. *Collaboration Skill Required* is whether the job posting requires collaboration skill. *Software Skills (Ratio)* is the ratio of software skills required in the job posting. *AI Adoption Rate* is the ratio of non-manager AI-related job postings in this plant. *Num. of All Jobs (Log)* is the log number of non-manager job postings in this plant. *Num. of All IT Jobs (Log)* is the log number of non-manager IT job posting in this plant. *Num. of All Required Skills (Log)* is the log number of all skills required in the job posting. *Full-Time Job* is an indicator equals to one when the job is a full time job. *MBA Required* equals to one when the job requires MBA degree. *Graduate Degree Required* equals to one when the job requires graduate degree or higher. *Minimum Work Experience (Log)* is the log minimum years of work experience required in the job posting. *Num. of Employees (Log)* is the log number of all employees in the firm. *Assets (Log)* and *Intangible Assets (Log)* are the log total assets and the log intangible assets, respectively, of the firm. *Property, Plant, and Equipment (Log)* is the log total property, plant, and equipment of the firm. *Market Value (Log)* is the log market value of the firm.

Table 2: Main Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Collaboration Skill Required				Software Skills (Ratio)			
AI Adoption Rate	0.02952***	0.02733***	0.02748***	0.02127***	0.02484**	0.02826***	0.02749***	0.01780***
	(0.00971)	(0.00955)	(0.00965)	(0.00577)	(0.00975)	(0.01031)	(0.01005)	(0.00463)
Num. of All Required Skills (Log)	0.03404***	0.03119***	0.03118***	0.03088***	0.02527***	0.02977***	0.02970***	0.02949***
	(0.00235)	(0.00229)	(0.00228)	(0.00092)	(0.00123)	(0.00126)	(0.00125)	(0.00047)
Full-Time Job		-0.00064	-0.00088	-0.00135		0.00622*	0.00591*	0.00425***
		(0.00332)	(0.00331)	(0.00093)		(0.00362)	(0.00354)	(0.00088)
MBA Required		0.01135***	0.01132***	0.01007***		-0.02005***	-0.02012***	-0.02051***
		(0.00216)	(0.00217)	(0.00125)		(0.00107)	(0.00108)	(0.00046)
Graduate Degree Required		0.00410	0.00408	0.00322		-0.01148***	-0.01146***	-0.01149***
		(0.00420)	(0.00421)	(0.00203)		(0.00279)	(0.00280)	(0.00089)
Minimum Work Experience		0.00106***	0.00106***	0.00094***		-0.00157***	-0.00157***	-0.00169***
		(0.00018)	(0.00018)	(0.00009)		(0.00014)	(0.00013)	(0.00004)
Num. of All Jobs			-0.00002	-0.00032***			-0.00026***	-0.00041**
			(0.00012)	(0.00012)			(0.00010)	(0.00017)
Num. of All IT Jobs			0.00084	0.00016			0.00160***	0.00195*
			(0.00081)	(0.00062)			(0.00046)	(0.00115)
Num. of Employees (Log)			-0.00056	-0.00002			-0.00191	-0.00230***
			(0.00275)	(0.00149)			(0.00156)	(0.00079)
Assets (Log)			0.00908**	0.00721**			0.00078	0.00239*
			(0.00456)	(0.00292)			(0.00329)	(0.00141)
Intangible Assets (Log)			-0.00121	-0.00046			-0.00087	-0.00107
			(0.00307)	(0.00176)			(0.00244)	(0.00088)
Property, Plant, and Equipment (Log)			-0.00665*	-0.00383			-0.00370	-0.00429***
			(0.00358)	(0.00260)			(0.00262)	(0.00156)
Market Value (Log)			0.00148	0.00085			0.00356**	0.00299***
			(0.00141)	(0.00090)			(0.00147)	(0.00053)
Constant	-0.05518***	-0.05243***	-0.06421***	-0.06629***	-0.01657***	-0.02583***	-0.01047	-0.00478
	(0.00698)	(0.00824)	(0.02424)	(0.01292)	(0.00385)	(0.00486)	(0.01497)	(0.00660)
Firm FE	Yes	Yes	Yes	No	Yes	Yes	Yes	No
MSA FE	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Plant (Firm × MSA) FE	No	No	No	Yes	No	No	No	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.049	0.049	0.049	0.066	0.115	0.126	0.126	0.161
Observations	4229590	4229590	4229590	4224250	4229590	4229590	4229590	4224250

Notes. Each observation is at job posting level. Only manager jobs (O*NET code: 11) are include in the analysis. All models report OLS regression coefficients with robust standard errors clustered at the firm and MSA level in parentheses. *Collaboration Skill Required* is whether the job posting requires collaboration skill. *Software Skills (Ratio)* is the ratio of software skills required in the job posting. $*p < 0.05$; $**p < 0.01$; $***p < 0.001$.

Table 3: Heterogeneity

	(1)	(2)	(3)	(4)
	Collaboration Skill Required		Software Skills (Ratio)	
Panel A:	*Near AI-Strong Univ or Not (Near = 1, Far Away = 0)*			
	˜ = 1	˜ = 0	˜ = 1	˜ = 0
AI Adoption Rate	0.02472*	0.01900*	0.03307**	0.01594*
	(0.01322)	(0.00982)	(0.01266)	(0.00821)
Adjusted R-squared	0.046	0.056	0.127	0.135
Observations	2536146	1693363	2536146	1693363
Panel B:	*Large Superstar Firm or Not (Star = 1, Not Star = 0)*			
	˜ = 1	˜ = 0	˜ = 1	˜ = 0
AI Adoption Rate	0.03366**	0.01277	0.03988***	0.00616
	(0.01457)	(0.00912)	(0.01451)	(0.00642)
Adjusted R-squared	0.044	0.064	0.122	0.142
Observations	2867529	1362038	2867529	1362038
Panel C:	*IT Firm or Not (IT = 1, Not IT = 0)*			
	˜ = 1	˜ = 0	˜ = 1	˜ = 0
AI Adoption Rate	0.03063	0.02616***	0.02651***	0.02675**
	(0.01889)	(0.00971)	(0.00839)	(0.01232)
Adjusted R-squared	0.047	0.050	0.122	0.124
Observations	912095	3317437	912095	3317437
Firm FE	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes. Each observation is at job posting level. Only manager jobs (O*NET code: 11) are include in the analysis. All models report OLS regression coefficients with robust standard errors clustered at the firm and MSA level in parentheses. *Collaboration Skill Required* is whether the job posting requires collaboration skill. *Software Skills (Ratio)* is the ratio of software skills required in the job posting. *Near AI-Strong Univ or No* is defined as whether there is an AI-strong university in the msa. *Large Superstar Firm or No* is an indicator equals to one when the firm is a superstar firm, which is defined as top 500 Compustat firms measured by market value. *IT Firm or Not* equals to one when the firm has NAICS code 51 or 54. All models include controls for time-varying characteristics of the plant (number of all job postings and number of all IT job postings), the job posting (log number of all required skills, full-time job or not, MBA required, graduate degree required, and minimum work experience), the firm (log number of employees, log total assets, log total intangible assets, log property, plant, and equipment, and log market value) and fixed effects (firm, msa, industry, occupation, month, and year). $*p < 0.05$; $**p < 0.01$; $***p < 0.001$.

Table 4: IV Estimation

	(1)	(2)	(3)	(4)
	Collaboration Skill Required		Software Skills (Ratio)	
AI Adoption Rate	0.68709***	0.49437***	0.20096**	0.19420**
	(0.23473)	(0.15326)	(0.09712)	(0.08327)
Num. of All Required Skills (Log)	0.03507***	0.03394***	0.03073***	0.03069***
	(0.00240)	(0.00229)	(0.00129)	(0.00125)
Full-Time Job	-0.00273	-0.00219	0.00543	0.00545
	(0.00392)	(0.00374)	(0.00350)	(0.00351)
MBA Required	0.01033***	0.01062***	-0.02038***	-0.02037***
	(0.00222)	(0.00218)	(0.00105)	(0.00105)
Graduate Degree Required	0.00328	0.00352	-0.01167***	-0.01166***
	(0.00418)	(0.00418)	(0.00281)	(0.00281)
Minimum Work Experience	0.00099***	0.00101***	-0.00159***	-0.00159***
	(0.00018)	(0.00018)	(0.00013)	(0.00013)
Num. of All Jobs	0.00139***	0.00098***	0.00011	0.00010
	(0.00045)	(0.00027)	(0.00022)	(0.00021)
Num. of All IT Jobs	-0.00430**	-0.00280**	0.00025	0.00030
	(0.00213)	(0.00140)	(0.00083)	(0.00077)
Num. of Employees (Log)	0.00216	0.00137	-0.00120	-0.00122
	(0.00394)	(0.00348)	(0.00177)	(0.00174)
Assets (Log)	0.01539*	0.01355*	0.00244	0.00237
	(0.00868)	(0.00743)	(0.00399)	(0.00398)
Intangible Assets (Log)	-0.00112	-0.00115	-0.00085	-0.00085
	(0.00575)	(0.00476)	(0.00247)	(0.00246)
Property, Plant, and Equipment (Log)	-0.02492**	-0.01958**	-0.00850*	-0.00832*
	(0.01017)	(0.00849)	(0.00477)	(0.00484)
Market Value (Log)	0.00015	0.00054	0.00321**	0.00323**
	(0.00311)	(0.00249)	(0.00159)	(0.00158)
Firm FE	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
IV	AI Adoption of Firms In 5-year Patent Network	AI Adoption of Firms In 3-year Patent Network	AI Adoption of Firms In 5-year Patent Network	AI Adoption of Firms In 3-year Patent Network
First Stage	0.12244***	0.11900***	0.12992***	0.12244***
F-Statistic	9.37	13.01	9.37	13.01
Adjusted R-squared	-0.010	-0.000	0.032	0.033
Observations	4229590	4229590	4229590	4229590

Notes. Each observation is at job posting level. Only manager jobs (O*NET code: 11) are include in the analysis. All models report IV-2SLS regression coefficients with robust standard errors clustered at the firm and MSA level in parentheses. The instrumental variable is the 5-year (or 3-year) average AI adoption rate of plants in the focal plants citation network within the 5 years (or 3 years) of the posting. *Collaboration Skill Required* is whether the job posting requires collaboration skill. *Software Skills (Ratio)* is the ratio of software skills required in the job posting. $*p < 0.05$; $**p < 0.01$; $***p < 0.001$.

Table 5: Mechanism Test - Team: Related Jobs and Unrelated Jobs

	(1) Collaboration Skill Required	(2) Software Skills (Ratio)
AI Adoption Rate (Only Related Jobs)	0.01452***	0.02833***
	(0.00466)	(0.00803)
AI Adoption Rate (Only Non-Related Jobs)	0.01080	0.01435**
	(0.00852)	(0.00609)
Firm FE	Yes	Yes
MSA FE	Yes	Yes
Industry FE	Yes	Yes
Occupation FE	Yes	Yes
Month FE	Yes	Yes
Year FE	Yes	Yes
Adjusted R-squared	0.049	0.127
Observations	4229590	4229590

Notes. Each observation is at job posting level. Only manager jobs (O*NET code: 11) are include in the analysis. All models report OLS regression coefficients with robust standard errors clustered at the firm and MSA level in parentheses. *Collaboration Skill Required* is whether the job posting requires collaboration skill. *Software Skills (Ratio)* is the ratio of software skills required in the job posting. *AI Adoption Rate (Only Related Jobs)* is the ratio of non-manager AI-related job postings in the related jobs for each manager occupation in the plant. The related jobs are obtained from O*NET. *AI Adoption Rate (Only Non-Related Jobs)* is the ratio of non-manager AI-related job postings in the non-related jobs for each manager occupation in the plant. All models include controls for time-varying characteristics of the plant (number of all job postings and number of all IT job postings), the job posting (log number of all required skills, full-time job or not, MBA required, graduate degree required, and minimum work experience), the firm (log number of employees, log total assets, log total intangible assets, log property, plant, and equipment, and log market value) and fixed effects (firm, msa, industry, occupation, month, and year). $*p < 0.05$; $**p < 0.01$; $***p < 0.001$.

Table 6: Mechanism Test - Team: Managers w. High/Low Team Build Duties

	(1)	(2)	(3)	(4)
	Collaboration Skill Required		Software Skills (Ratio)	
	Team Build = 1	Team Build = 0	Team Build = 1	Team Build = 0
AI Adoption Rate (Only Related Jobs)	0.02073***	0.00445	0.03412***	0.01214*
	(0.00798)	(0.00579)	(0.01025)	(0.00633)
AI Adoption Rate (Only Non-Related Jobs)	0.01607	0.01930**	0.00714	0.00808
	(0.01253)	(0.00838)	(0.00944)	(0.00545)
Firm FE	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.049	0.069	0.136	0.159
Observations	2089768	1322338	2089768	1322338

Notes. Each observation is at job posting level. Only manager jobs (O*NET code: 11) are include in the analysis. All models report OLS regression coefficients with robust standard errors clustered at the firm and MSA level in parentheses. *Collaboration Skill Required* is whether the job posting requires collaboration skill. *Software Skills (Ratio)* is the ratio of software skills required in the job posting. *AI Adoption Rate (Only Related Jobs)* is the ratio of non-manager AI-related job postings in the related jobs for each manager occupation in the plant. The related jobs are obtained from O*NET. *AI Adoption Rate (Only Non-Related Jobs)* is the ratio of non-manager AI-related job postings in the non-related jobs for each manager occupation in the plant. *Team build* is an indicator variable which equals one if the job has higher than 60 level (out of 100) in O*NET work activity "Developing and Building Teams". All models include controls for time-varying characteristics of the plant (number of all job postings and number of all IT job postings), the job posting (log number of all required skills, full-time job or not, MBA required, graduate degree required, and minimum work experience), the firm (log number of employees, log total assets, log total intangible assets, log property, plant, and equipment, and log market value) and fixed effects (firm, msa, industry, occupation, month, and year). $*p < 0.05$; $**p < 0.01$; $***p < 0.001$.

Table 7: Mechanism Test - Team: Different Ways of Hiring AI Workers

	(1)	(2)	(3)	(4)
	Collaboration Skill Required		Software Skills (Ratio)	
	IT Managers Included	IT Managers Excluded	IT Managers Included	IT Managers Excluded
AI Adoption Rate in IT Workers (Only Related Jobs)	0.01441***	0.01321**	0.01915***	0.01758***
	(0.00547)	(0.00569)	(0.00511)	(0.00435)
AI Adoption Rate in Non-IT Workers (Only Related Jobs)	-0.00013	0.00067	0.00858	0.01087
	(0.00874)	(0.00914)	(0.00704)	(0.00662)
AI Adoption Rate (Only Non-Related Jobs)	0.02522**	0.02368*	0.02791***	0.02497***
	(0.01235)	(0.01219)	(0.00916)	(0.00899)
Firm FE	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.051	0.052	0.150	0.146
Observations	1952059	1892179	1952059	1892179

Notes. Each observation is at job posting level. Only manager jobs (O*NET code: 11) with relation to IT workers (O*NET code: 15.12) are include in the analysis. All models report OLS regression coefficients with robust standard errors clustered at the firm and MSA level in parentheses. *Collaboration Skill Required* is whether the job posting requires collaboration skill. *Software Skills (Ratio)* is the ratio of software skills required in the job posting. *AI Adoption Rate in IT Workers (Only Related Jobs)* is the ratio of AI-related job postings in the IT engineer jobs (O*NET code: 15-12), and *AI Adoption Rate in Non-IT Workers (Only Related Jobs)* is the ratio of AI-related job postings in the Non-IT engineer jobs. All models include controls for time-varying characteristics of the plant (number of all job postings and number of all IT job postings), the job posting (log number of all required skills, full-time job or not, MBA required, graduate degree required, and minimum work experience), the firm (log number of employees, log total assets, log total intangible assets, log property, plant, and equipment, and log market value) and fixed effects (firm, msa, industry, occupation, month, and year). $*p < 0.05$; $**p < 0.01$; $***p < 0.001$.

Table 8: Mechanism Test - Team: Corporate Culture

	(1)	(2)	(3)	(4)
	Collaboration Skill Required		Software Skills (Ratio)	
AI Adoption Rate	0.04152***	0.04567***	0.01248	0.00568
	(0.00899)	(0.01099)	(0.00847)	(0.00684)
GoodTeamWorkCulture	-0.00041		-0.00017	
	(0.00150)		(0.00078)	
GoodTeamWorkCulture × AI Adoption Rate	-0.02515*		0.02691**	
	(0.01322)		(0.01157)	
GoodInnovationCulture		0.00029		-0.00169
		(0.00137)		(0.00110)
GoodInnovationCulture × AI Adoption Rate		-0.02463		0.02971**
		(0.01527)		(0.01292)
Firm FE	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.049	0.049	0.126	0.126
Observations	4229590	4229590	4229590	4229590

Notes. Each observation is at job posting level. Only manager jobs (O*NET code: 11) are include in the analysis. All models report OLS regression coefficients with robust standard errors clustered at the firm and MSA level in parentheses. *Collaboration Skill Required* is whether the job posting requires collaboration skill. *Software Skills (Ratio)* is the ratio of software skills required in the job posting. *GoodTeamWorkCulture* is score of team work corporate culture is greater than the median. *GoodInnovationCulture* is the score of innovation corporate culture is greater than the median. All models include controls for time-varying characteristics of the plant (number of all job postings and number of all IT job postings), the job posting (log number of all required skills, full-time job or not, MBA required, graduate degree required, and minimum work experience), the firm (log number of employees, log total assets, log total intangible assets, log property, plant, and equipment, and log market value) and fixed effects (firm, msa, industry, occupation, month, and year). $*p < 0.05$; $**p < 0.01$; $***p < 0.001$.

Table 9: Mechanism Test - Org.: Exclude Flattened Organizations

	(1)	(2)	(3)	(4)
	Collaboration Skill Required		Software Skills (Ratio)	
AI Adoption Rate	0.02674***		0.02724**	
	(0.01030)		(0.01085)	
AI Adoption Rate (Only Related Jobs)		0.01566***		0.03010***
		(0.00479)		(0.00832)
AI Adoption Rate (Only Non-Related Jobs)		0.00848		0.01194*
		(0.00879)		(0.00617)
Firm FE	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.050	0.050	0.126	0.126
Observations	3875717	3875717	3875717	3875717

Notes. Each observation is at job posting level. We exclude firms with organization hierarchy decrease two levels or more. Only manager jobs (O*NET code: 11) are include in the analysis. All models report OLS regression coefficients with robust standard errors clustered at the firm and MSA level in parentheses. *Collaboration Skill Required* is whether the job posting requires collaboration skill. *Software Skills (Ratio)* is the ratio of software skills required in the job posting. All models include controls for time-varying characteristics of the plant (number of all job postings and number of all IT job postings), the job posting (log number of all required skills, full-time job or not, MBA required, graduate degree required, and minimum work experience), the firm (log number of employees, log total assets, log total intangible assets, log property, plant, and equipment, and log market value) and fixed effects (firm, msa, industry, occupation, month, and year). $*p < 0.05$; $**p < 0.01$; $***p < 0.001$.

Table 10: Mechanism Test - Org.: Exclude Organizations w. Changes in Span of Control

	(1)	(2)	(3)	(4)
	Collaboration Skill Required		Software Skills (Ratio)	
AI Adoption Rate	0.01819		0.01663**	
	(0.01306)		(0.00706)	
AI Adoption Rate (Only Related Jobs)		0.01185**		0.02924***
		(0.00537)		(0.00712)
AI Adoption Rate (Only Non-Related Jobs)		0.00408		0.00899
		(0.01207)		(0.00591)
Firm FE	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.050	0.050	0.115	0.115
Observations	2729104	2729104	2729104	2729104

Notes. Each observation is at job posting level. We exclude firms with span of control (number of workers over managers) change more than one standard deviation or more. Only manager jobs (O*NET code: 11) are include in the analysis. All models report OLS regression coefficients with robust standard errors clustered at the firm and MSA level in parentheses. *Collaboration Skill Required* is whether the job posting requires collaboration skill. *Software Skills (Ratio)* is the ratio of software skills required in the job posting. All models include controls for time-varying characteristics of the plant (number of all job postings and number of all IT job postings), the job posting (log number of all required skills, full-time job or not, MBA required, graduate degree required, and minimum work experience), the firm (log number of employees, log total assets, log total intangible assets, log property, plant, and equipment, and log market value) and fixed effects (firm, msa, industry, occupation, month, and year). $*p < 0.05$; $**p < 0.01$; $***p < 0.001$.

Table 11: Mechanism Test - Direct Exposure: Add Managers' Own AI Adoption

	(1)	(2)	(3)	(4)
	Collaboration Skill Required		Software Skills (Ratio)	
AI Adoption Rate	0.02872***		0.00541	
	(0.00942)		(0.00583)	
AI Adoption Rate (Only Related Jobs)		0.01516***		0.01622***
		(0.00408)		(0.00426)
AI Adoption Rate (Only Non-Related Jobs)		0.01183		0.00486
		(0.00843)		(0.00476)
AI Adoption Rate (Managers)	-0.01456**	-0.01393**	0.07281***	0.07014***
	(0.00635)	(0.00639)	(0.01358)	(0.01338)
Firm FE	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.049	0.049	0.126	0.126
Observations	4169714	4169714	4169714	4169714

Notes. Each observation is at job posting level. Only manager jobs (O*NET code: 11) are include in the analysis. All models report OLS regression coefficients with robust standard errors clustered at the firm and MSA level in parentheses. *Collaboration Skill Required* is whether the job posting requires collaboration skill. *Software Skills (Ratio)* is the ratio of software skills required in the job posting. All models include controls for time-varying characteristics of the plant (number of all job postings and number of all IT job postings), the job posting (log number of all required skills, full-time job or not, MBA required, graduate degree required, and minimum work experience), the firm (log number of employees, log total assets, log total intangible assets, log property, plant, and equipment, and log market value) and fixed effects (firm, msa, industry, occupation, month, and year). $*p < 0.05$; $**p < 0.01$; $***p < 0.001$.

Table 12: Further Investigation: Skills and Salary

	(1)	(2)	(3)	(4)	(5)	(6)
				Salary		
Collaboration Skill Required	5,731.89596**	5,717.89565**	10,760.38042**			
	(2,254.97018)	(2,489.48841)	(4,287.83221)			
Software Skills (Ratio)				-51176.32934***	-50201.28634***	-36341.28654
				(15,064.17535)	(15,601.59706)	(26,450.78345)
Collaboration Skill Required × MBA Required		101.48634				
		(4,924.47217)				
Collaboration Skill Required × Minimum Work Experience			-890.01941			
			(563.30550)			
Software Skills (Ratio) × MBA Required					-20782.88955	
					(17,074.34583)	
Software Skills (Ratio) × Minimum Work Experience						-3,408.77383
						(3,128.70313)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.457	0.457	0.457	0.460	0.460	0.460
Observations	160772	160772	160772	160772	160772	160772

Notes. Each observation is at job posting level. Only manager jobs (O*NET code: 11) and job postings with salary information are include in the analysis. All models report OLS regression coefficients with robust standard errors clustered at the firm and MSA level in parentheses. *MBA Required* equals to one when the job requires MBA degree. *Minimum Work Experience* is the minimum years of work experience required in the job posting. *Collaboration Skill Required* is whether the job posting requires collaboration skill. *Software Skills (Ratio)* is the ratio of software skills required in the job posting. *Software Skills (Log)* is the log number of software skills required in the job posting. All models include controls for time-varying characteristics of the plant (number of all job postings and number of all IT job postings), the job posting (log number of all required skills, full-time job or not, MBA required, graduate degree required, and minimum work experience), the firm (log number of employees, log total assets, log total intangible assets, log property, plant, and equipment, and log market value) and fixed effects (firm, msa, industry, occupation, month, and year). $*p < 0.05$; $**p < 0.01$; $***p < 0.001$.

Appendix

Table A.1: Collaboration Skills

Skill Name	Frequency	Co-occurrence w. Collaboration	Co-occurrence Rate
Panel A: Collaboration Skills			
Collaboration	166869	166869	1
Cross-Functional Collaboration	26155	1892	0.07
Cloud Collaboration	434	22	0.05
Interdisciplinary Collaboration	109	21	0.19
Project Collaboration	505	56	0.11
Social Collaboration	560	45	0.08
Supply Chain Collaboration	184	7	0.04
Virtual Collaboration	874	16	0.02
Panel B: Other Related Skills			
Coordinating	548887	23787	0.04
Teamwork	239049	14492	0.06
Cooperation	54162	1765	0.04
Project Coordination	31750	806	0.02
Care Coordination	17517	366	0.02
Cross-Functional Coordination	5596	307	0.06
Motor Coordination	4199	45	0.02
Maintenance Coordination	3798	30	0.00
Training Coordination	1959	72	0.04
Clinical Research Coordination	1561	24	0.02
Construction Coordination	606	7	0.02

Notes. This table shows the frequency of different skills and co-occurrence with collaboration skill

Table A.2: Robustness Check: Other Measurement of Collaboration Skills

	(1)	(2)	(3)	(4)
	Collaboration Skill Required			
	Collaboration Skills	Only Collaboration	Collaboration+Teamwork	Collaboration Skills+Teamwork
AI Adoption Rate	0.02748***	0.02377***	0.03447*	0.03770*
	(0.00965)	(0.00836)	(0.01952)	(0.01930)
Num. of All Required Skills (Log)	0.03118***	0.02671***	0.06856***	0.07237***
	(0.00228)	(0.00201)	(0.00347)	(0.00366)
Full-Time Job	-0.00088	-0.00105	-0.01623	-0.01605
	(0.00331)	(0.00303)	(0.01072)	(0.01080)
MBA Required	0.01132***	0.00851***	0.00682**	0.00938***
	(0.00217)	(0.00222)	(0.00344)	(0.00343)
Graduate Degree Required	0.00408	0.00155	-0.00115	0.00083
	(0.00421)	(0.00389)	(0.00470)	(0.00483)
Minimum Work Experience	0.00106***	0.00089***	0.00049	0.00065**
	(0.00018)	(0.00016)	(0.00031)	(0.00032)
Num. of All Jobs	-0.00002	0.00001	0.00024	0.00019
	(0.00012)	(0.00013)	(0.00018)	(0.00017)
Num. of All IT Jobs	0.00084	0.00062	-0.00022	0.00004
	(0.00081)	(0.00070)	(0.00105)	(0.00115)
Num. of Employees (Log)	-0.00056	-0.00008	-0.00463	-0.00494
	(0.00275)	(0.00234)	(0.00412)	(0.00442)
Assets (Log)	0.00908**	0.00769*	0.01788	0.01881*
	(0.00456)	(0.00407)	(0.01101)	(0.01088)
Intangible Assets (Log)	-0.00121	-0.00111	-0.00315	-0.00336
	(0.00307)	(0.00280)	(0.00508)	(0.00518)
Property, Plant, and Equipment (Log)	-0.00665*	-0.00784**	-0.00965*	-0.00825
	(0.00358)	(0.00334)	(0.00546)	(0.00556)
Market Value (Log)	0.00148	0.00186	0.00103	0.00081
	(0.00141)	(0.00127)	(0.00445)	(0.00439)
Constant	-0.06421***	-0.05533***	-0.08340**	-0.09185**
	(0.02424)	(0.02081)	(0.03775)	(0.03994)
Firm FE	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.049	0.046	0.070	0.072
Observations	4229590	4229590	4229590	4229590

Notes. Each observation is at job posting level. Only manager jobs (O*NET code: 11) are include in the analysis. All models report OLS regression coefficients with robust standard errors clustered at the firm and MSA level in parentheses. *Collaboration Skill Required* is whether the job posting requires collaboration skill. *Collaboration Skills* is any skill that contains collaboration, *Only Collaboration* is only collaboration, *Collaboration+Teamwork* is only collaboration and teamwork skill, and *Collaboration Skills+Teamwork* is any skill that contains collaboration and teamwork. $*p < 0.05$; $**p < 0.01$; $***p < 0.001$.

Table A.3: Robustness Check: Falsification Test

	(1) Cross-Functional Skills Required	(2) Common Skills (Ratio)
AI Adoption Rate	0.00353	-0.11967***
	(0.00777)	(0.02473)
Num. of All Required Skills (Log)	0.01620***	0.00200
	(0.00144)	(0.00725)
Full-Time Job	0.00894	0.00123
	(0.00646)	(0.01030)
MBA Required	0.02419***	-0.01035***
	(0.00233)	(0.00316)
Graduate Degree Required	0.00054	-0.02560***
	(0.00292)	(0.00342)
Minimum Work Experience	0.00099***	-0.00074**
	(0.00019)	(0.00036)
Num. of All Jobs	0.00021	0.00027
	(0.00040)	(0.00017)
Num. of All IT Jobs	0.00110	-0.00255*
	(0.00085)	(0.00145)
Num. of Employees (Log)	-0.00427*	0.00275
	(0.00232)	(0.00487)
Assets (Log)	0.00204	0.00728
	(0.00406)	(0.00845)
Intangible Assets (Log)	0.00177	-0.00119
	(0.00311)	(0.00434)
Property, Plant, and Equipment (Log)	0.00307	-0.00367
	(0.00261)	(0.00416)
Market Value (Log)	-0.00035	-0.00436
	(0.00148)	(0.00331)
Constant	-0.00901	0.38770***
	(0.01910)	(0.03976)
Firm FE	Yes	Yes
MSA FE	Yes	Yes
Industry FE	Yes	Yes
Occupation FE	Yes	Yes
Month FE	Yes	Yes
Year FE	Yes	Yes
Adjusted R-squared	0.038	0.188
Observations	4229590	4229590

Notes. Each observation is at job posting level. Only manager jobs (O*NET code: 11) are include in the analysis. All models report OLS regression coefficients with robust standard errors clustered at the firm and MSA level in parentheses. *Cross-Functional Skills Required* is whether the job posting requires the managers to work cross functions. *Common Skills (Ratio)* is the ratio of common (soft) skills. $*p < 0.05$; $**p < 0.01$; $***p < 0.001$.

Table A.4: Robustness Check: Other Measurement of AI Adoption

	(1)	(2)	(3)	(4)	(5)	(6)
	Collaboration Skill Required			Software Skills (Ratio)		
AI Adoption Rate (Key Words)	0.03733***			0.02531***		
	(0.00910)			(0.00597)		
AI Adoption Rate (w. Managers)		0.04225*			0.09066***	
		(0.02388)			(0.02609)	
Num. of All AI Jobs (Log)			0.00382***			0.00161***
			(0.00051)			(0.00030)
Num. of All Required Skills (Log)	0.03070***	0.03100***	0.03123***	0.02932***	0.02950***	0.02963***
	(0.00230)	(0.00228)	(0.00229)	(0.00123)	(0.00123)	(0.00123)
Full-Time Job	-0.00100	-0.00086	-0.00118	0.00586*	0.00587*	0.00583*
	(0.00329)	(0.00330)	(0.00328)	(0.00353)	(0.00353)	(0.00353)
MBA Required	0.01120***	0.01133***	0.01101***	-0.02019***	-0.02015***	-0.02023***
	(0.00217)	(0.00216)	(0.00216)	(0.00109)	(0.00108)	(0.00108)
Graduate Degree Required	0.00406	0.00405	0.00371	-0.01147***	-0.01157***	-0.01160***
	(0.00421)	(0.00421)	(0.00423)	(0.00279)	(0.00280)	(0.00280)
Minimum Work Experience	0.00104***	0.00106***	0.00102***	-0.00158***	-0.00158***	-0.00159***
	(0.00018)	(0.00018)	(0.00018)	(0.00013)	(0.00013)	(0.00013)
Num. of All Jobs	0.00015	-0.00000	-0.00033***	-0.00016	-0.00014	-0.00042***
	(0.00013)	(0.00014)	(0.00010)	(0.00010)	(0.00009)	(0.00015)
Num. of All IT Jobs	0.00012	0.00071	-0.00062	0.00118***	0.00108***	0.00111***
	(0.00079)	(0.00084)	(0.00068)	(0.00044)	(0.00039)	(0.00040)
Num. of Employees (Log)	-0.00031	-0.00049	-0.00080	-0.00178	-0.00165	-0.00208
	(0.00280)	(0.00275)	(0.00271)	(0.00157)	(0.00159)	(0.00155)
Assets (Log)	0.00936**	0.00911**	0.00939**	0.00088	0.00115	0.00075
	(0.00458)	(0.00456)	(0.00467)	(0.00324)	(0.00326)	(0.00320)
Intangible Assets (Log)	-0.00131	-0.00122	-0.00169	-0.00094	-0.00088	-0.00107
	(0.00309)	(0.00307)	(0.00314)	(0.00244)	(0.00233)	(0.00245)
Property, Plant, and Equipment (Log)	-0.00638*	-0.00679*	-0.00623*	-0.00327	-0.00487*	-0.00308
	(0.00354)	(0.00348)	(0.00333)	(0.00244)	(0.00283)	(0.00235)
Market Value (Log)	0.00125	0.00145	0.00117	0.00343**	0.00343**	0.00347**
	(0.00142)	(0.00141)	(0.00142)	(0.00150)	(0.00149)	(0.00148)
Constant	-0.06876***	-0.06373***	-0.06811***	-0.01303	-0.01134	-0.01116
	(0.02478)	(0.02434)	(0.02429)	(0.01515)	(0.01488)	(0.01498)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.049	0.049	0.050	0.126	0.127	0.126
Observations	4229590	4229590	4229590	4229590	4229590	4229590

Notes. Each observation is at job posting level. Only manager jobs (O*NET code: 11) are include in the analysis. All models report OLS regression coefficients with robust standard errors clustered at the firm and MSA level in parentheses. *Collaboration Skill Required* is whether the job posting requires collaboration skill. *Software Skills (Ratio)* is the ratio of software skills required in the job posting. *AI Adoption Rate (Key Words)* is the ratio of non-manager AI-related job postings, measured by AI-related key words in skills, in this plant. *AI Adoption Rate (w. Managers)* is the ratio of manager and non-manager AI-related job postings in this plant. $*p < 0.05$; $**p < 0.01$; $***p < 0.001$.