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AI technology application and employee responsibility

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Employees are important stakeholders of firms, and employee responsibility is a crucial dimension of corporate social responsibility. This study employed a multivariable linear regression model to analyze the impact of AI technology on the variation in employee responsibility. We also utilized multiple methods, such as propensity score matching and alternative indicator analysis, to ensure the robustness of the research results. We theorized and found that the application of AI technology has a negative effect on employee responsibility, with supervision cost partially mediating the relationship between AI technology application and employee responsibility. Moreover, the negative relationship between AI technology application and employee responsibility decreases as the level of product market competition in which the firm operates increases, and it is stronger in government-controlled firms than in privately controlled firms. We also found that AI technology application and employee responsibility can improve firm productivity, and employee responsibility has a significant positive impact on innovation output and innovation efficiency, while the application of AI technology does not significantly impact innovation output and innovation efficiency. Our study contributes to research on the impact of AI technology in the workplace and has important implications for organizational practices regarding the application of AI technology and employee responsibility.

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Introduction

In recent years, the rapid development of Artificial Intelligence (AI) technology has become the theme of the future era. The deep integration of AI with industry has not only significantly changed the macro environment of firms, but also profoundly affected their organizational structures, productivity, and micro-level decision-making (Agrawal et al., 2019a; Agrawal et al., 2019b; Cockburn et al., 2019; Vincent, 2021; Gries, Naudé (2018); Swart and Kinnie, 2014; Duggan et al., 2020; Tong et al., 2021). AI is a field of computer science that aims to understand the fundamental principles of intelligence and develop innovative intelligent machines capable of exhibiting cognitive abilities similar to humans. Research in this field encompasses robotics, language and image recognition, natural language processing, and expert systems (Bawack et al., 2021). AI technology has gradually moved out of the laboratory and into the firm internal production and operation, management practices, and support technology. For example, in the financial industry, managers attempt to use AI technology to make better and faster decisions to increase revenue and reduce costs (Wisskirchen et al., 2017). In personnel management, managers also expect to improve employee performance through AI technology (such as performance monitoring applications) (Tong et al., 2021).

Much of the previous research on the impact of AI applications on economic outcomes has focused on employment and productivity. Based on the potential of the technology, there are two views on the relationship between AI technology and employment: replacement and augmentation views (Frey and Osborne, 2017; Daugherty and Wilson, 2018; Tschang and Almirall, 2021). The influence of AI technology on labor productivity also has two viewpoints. Literature supporting positive effects suggests that AI can automate work tasks, reduce uncertainty, and lead to the recombination of existing and generation of new innovations (Agrawal et al., 2019a; Agrawal et al., 2019b; Cockburn et al., 2019). In contrast, some other theoretical model predicted that the continuous productivity slowdown may persist due to the increasing inequality (Gries, Naudé, 2018), rising learning costs (Jones, 2009), and the lower disruption rate of AI compared to other general technologies (Gordon, 2016, 2018).

At the same time, the application of AI technology in firms also brings significant challenges to management practice. When using digital technologies such as AI, many organizations encounter the "disillusionment" of their ideal expectations (Xie et al., 2021), and there are many unsatisfactory aspects, which not only fail to bring positive effects, but also lead to a series of negative consequences such as reduced staff organizational commitment and career satisfaction, as well as increased employee job insecurity and turnover intention (Li et al., 2019; Bhargava et al., 2021; Chui et al., 2015; Brougham and Haar, 2018). These research findings are primarily from the perspective of employee perception, that is, the application of artificial intelligence technology in firms makes employees feel insecure or under great pressure about their future job prospects, and thus results in a higher turnover intention.

The application of AI technology in the workplace also has profound social and political implications. In digital critical research, many scholars have pointed out that automation has reduced the low and middle skilled jobs and widened the income gap between the middle and high skilled jobs (Goyal and Aneja, 2020; Servoz, 2019; Xie et al., 2021). Unless effective mitigation policies are implemented, the increasing popularity of AI will exacerbate existing inequalities in society (Raisch and Krakowski, 2021; Servoz, 2019; Makridakis, 2017; Eubanks, 2018). Furthermore, there are numerous legal and human rights challenges associated with AI, such as surveillance, algorithmic transparency, privacy, and discrimination (Aizenberg and van den Hoven, 2020; Schlund and Zitek, 2021; Rodrigues, 2020; Coglianese and Lehr, 2019; Köchling and Wehner, 2020; Todolí-Signes, 2019; Kim and Bodie, 2021). Although these urgent challenges have received increasing attention in recent years, solutions to these complex problems are often developed without empirical research and lack the participation of stakeholders affected by technology (Aizenberg and van den Hoven, 2020).

Based on behavioral science theory, employees are important resources and assets of firms. The realization of business objectives and improvement of production efficiency depends on the joint efforts of all employees. Treating employees well and taking responsibility for them is conducive to establishing a mutually beneficial relationship between firm and its employees (Brammer et al., 2007; Skudiene and Auruskeviciene, 2012; Chun, 2009; Gharleghi et al., 2018), enhancing firm innovation and labor productivity (Jones, 1995), and bringing competitive advantages to the firm (Harrison et al., 2010). Employees are important stakeholders of firms, and employee responsibility is a crucial dimension of corporate social responsibility (CSR) (Clarkson, 1995). According to Turoń (2016) and Clarke (1998), CSR towards employees should include offering decent salaries appropriate for employee engagement in the firm's development, providing opportunities for the possibility of development, participation in courses, and career development, and ensuring working conditions for achieving organizational objectives and outputs, that are safe, healthy, and enjoyable.

However, based on the firm's micro-level data, there is a relative scarcity of research on the impact of AI technology on employee responsibility from the perspective of human resource management objects, management ideas, and management methods. This study seeks to address this gap. Through our research, we hope to not only contribute to enrichment of this field of study but also provide a new interpretation perspective for many inconsistent conclusions in the literature.

The interests of managers and employees are not completely aligned, and there is information asymmetry between them. The relationship between managers and employees can be considered as a kind of principal-agent relationship (Chen and Jiang, 2002; Anderson and Oliver, 1987; Banker et al., 1996; Deckop et al., 1999; Eisenhardt, 1988). To address and mitigate the agency problem, it is necessary to establish a mechanism that aligns the agent's behavior consistent with the principal's interests. Modern economics provides two alternative modes for achieving this: direct supervision of employees or providing incentives to employees through subtle contracts (Fong and Tosi, 2007).

Employee responsibility is an important incentive method for firms (Skudiene and Auruskeviciene, 2012), and serves as a reward for employees (Liu et al., 2020). For example, when employees work in an organization, they can receive various forms of financial reward such as salary and welfare, as well as non-financial reward such as good working environment, respect and recognition, and opportunities for learning and growth (Liu et al., 2020). These rewards generate both extrinsic and intrinsic incentives for employees (Skudiene and Auruskeviciene, 2012). Many previous studies have shown that employee-related corporate social responsibilities have a positive impact on employee satisfaction, loyalty, innovation, and labor efficiency (Chun, 2009; Liu et al., 2020; Wu and Zhang, 2021; Jones, 1995; Gharleghi et al., 2018). Skudiene and Auruskeviciene (2012) proposed that employers can use corporate social responsibility profile as a device to improve employee motivation. From previous research, we believe that corporate social responsibility, as an incentive tool, effectively solves the agency problem between the principal and the agent, and the conflicting interests between the principal and the agent tend to be reconciled. When it is difficult to supervise agents or the cost of supervising agents is high, the motivation of firms to reduce agency costs through incentives will continue to increase (Chen and Jiang, 2002).

AI technology can be integrated into multiple subsystems of large systems as needed. For example, it can be implemented in the production of "thinking machines" that can imitate, learn from, and even surpass human intelligence. In addition, AI can facilitate information exchange between various entities in the supply chain and replace traditional assets, such as inventory, facilities, and transportation equipment, with digital alternatives. This technology can also aid companies in connecting with their customers, suppliers, and other partners along the supply chain (Min, 2010). It can also be applied to equipment and processes, for example, to automatically perceive and collect working condition information, and to automatically adjust and optimize processing parameters according to real-time status. AI can also be embedded in human resource management, including predicting turnover rates using artificial neural networks, searching for candidates using a knowledge base system, creating employee schedules using genetic algorithms, analyzing employee emotions through text mining, and enabling employee self-service with features such as resume data collection and interactive voice response (Chang, 2020; Strohmeier and Piazza, 2015; Tong et al., 2021). Whether employees assign tasks to robots, supervise the normal operation of robots, or AI assigns tasks to people and monitors their work, they all represent a form of resource allocation within a large system, aiming to efficiently achieve organizational goals.

AI technology not only redefines the object of human resource management (Xu and Xu, 2020), but also shapes a new environmental structure in many dimensions, such as management idea, supervision, and incentive. With the continuous development and widespread application of AI technology, more and more "artificial intelligence employees" are entering firms to replace humans in certain jobs partially or completely, thus impacting the management idea of "social people" (Xu and Xu, 2020). In addition, the application of AI technology not only provides strong data support for a firm's decision-making, but also greatly improves labor efficiency and reduces supervision cost (Tong et al., 2021), which may change the way firms solve agency problems. Before the popularization and application of AI technology, many activities in firms were difficult or very expensive to implement. The costs of robots with high-precision dexterity are falling significantly (Frey and Osborne, 2017). We think that the application of AI technology will inevitably affect the attitudes and ways firms treat employees, and their willingness to take the responsibility for their employees.

This study focus on the following issues: in the context of the rapid development of digital economy, how does the application of AI technology affect employee responsibility? Does the institutional environment (such as product market competition, government ownership) moderate the relationship between them? If application of AI technology is positively associated with employee responsibility, what is the possible mediator in this relationship? To answer the above questions, this study, based on agency theory and behavioral science theory, takes China's listed manufacturing companies in Shanghai and Shenzhen A shares from 2011 to 2020 as the research sample and examines the relationship between the application of AI technology and employee responsibility, as well as the moderating (product market competition, government ownership) and mediating (supervision cost) effect in this relationship. Moreover, if the application of AI technology is found to have a positive relationship with firm's labor productivity, does it imply that "people-oriented" principle and employee responsibility are meaningless for the long-term development of firms in the era of artificial intelligence? This study also compares the effects of the application of AI technology and employee responsibility on labor productivity and innovation performance.

Theory and research hypothesis

Theoretical basis

Behavioral science theory. At the end of 19th century and the beginning of 20th century, with economic development and social progress, people found that scientific management theory could not solve all problems in practice. The scientific management theory assumes that people are "economic people", with a one-sided emphasis on the stimulus role of money, while ignoring people's social needs. Numerous issues in management practice are intertwined with human factors, as people's actions and conduct are likely to shift over time and in various settings (Stephen et al., 2008). To adapt to the trend of development, many thinkers, and practitioners in the field of management began to study new management theories.

Elton Mayo's Hawthorne experiment found that the change of working conditions was not directly related to the increase in workers' output. The social relationship between management and employees and the relationship among employees are important factors affecting labor efficiency. The behavior of informal organizations will have an impact on labor efficiency (Mayo, 1946).

Based on this, Mayo put forward the interpersonal theory that workers are "social people" and that informal organizations exist in firms. The new leadership is about improving the satisfaction of employees, to stimulate their enthusiasm for work. Later, with the continuous understanding and application of interpersonal relationship theory, researchers began to study human behavior from three different levels: individual, group and organization (Stephen et al., 2008). Each level has formed various types and factions because of different research angles and priorities. The main types are human nature hypothesis theory (Mayo, 1946), incentive theory (Maslow, 1954; Atkinson, Feather, 1966; Herzberg, 1968), group behavior theory (Arrow et al., 2000) and leadership behavior theory (Ahmed Khan et al., 2016; Yukl, 2006). The first two theories focus on the study of individual behavior, while the last two theories focus on the study of groups and organizations.

Overall, behavioral science theory advocates a "people-oriented" approach, emphasizing the importance of the relationship between organizations and employees, internal communication, and employees' participation in management. It posits that talent is the continuous driving force for enterprise development (Mayo, 1946). Managers must understand the motivation behind people's behavior to effectively manage them and tap into their potential. An excellent manager should not only care about production but also care for employees (Yukl, 2006). To fully utilize people's initiative and creativity, it is essential to first satisfy employees and pay attention to meeting their various needs (Herzberg, 1968; Yukl, 2006).

Agency theory. Agency theory was first put forward by Jensen and Meckling in 1976. Jensen and Meckling stated that "agency costs arise in any situation involving cooperative effort, such as the coauthoring of this article by two or more people" (Jensen, Meckling, 1976). Agency theory has been widely applied to various levels of employees, including lower-level employees (Anderson and Oliver, 1987; Banker et al., 1996; Deckop et al., 1999; Eisenhardt, 1988). The issue of agency problems is not exclusive to CEOs and owners but is rather a common phenomenon (Fong and Tosi, 2007). This study focuses on the agency cost caused by agency conflict between managers and employees.

Employees are the end of agency chain, and their enthusiasm and ability directly affect firm efficiency. The principal-agent problem between managers and employees refers to the conflict of interest that arises when the goals of the principal (the manager) and the agent (the employee) are not aligned (Anderson and Oliver, 1987; Banker et al., 1996; Deckop et al., 1999; Eisenhardt, 1988). The manager may seek to maximize the firm's profits, while the employee may seek to maximize their own personal interests, such as salary or job security (Anderson and Oliver, 1987). This misalignment of interests can result in the employee engaging in behaviors that are not in the best interests of the firm, such as shirking, or failing to put in the necessary effort to complete tasks. If it were possible to observe employee actions more precisely, or if there were no information asymmetry between employees and managers, the principal-agent problem would not arise (Banker et al., 1996). The information asymmetry allows the agent to misrepresent their abilities to the principal (i.e., adverse selection) and/or shirk (i.e., moral hazard) (Fong and Tosi, 2007). When employees believe that their efforts have not been recognized, or that their slacking or "hitchhiking" behavior has not been punished, or that their personal potential and ideals are difficult to realize, they may reduce their existing efforts (Chen and Jiang, 2002).

There are two main solutions to the principal-agent problem between managers and employees: increasing effectiveness of monitoring employees and aligning incentives between managers and employees (Fong and Tosi, 2007). Fama (1980) pointed out that if there is no supervision, the agent's opportunistic behavior will become a more reasonable result, and strict supervision can reduce the deviation of the agent's behavior. However, this method may not be suitable if the supervision cost is too high, or if the agent's behavior is difficult to judge (Chen and Jiang, 2002). Based on the principle of utility maximization, the agent's utility is the agent's compensation function (Groff and Wright, 1989). To motivate agents to perform actions that maximize the principal's utility, the principal must effectively motivate agents (Stroh et al., 1996). Under an effective incentive mechanism, rational actors should forgo opportunistic behavior.

AI technology application and employee responsibility. Currently, in order to enhance competitiveness, an increasing number of firms are incorporating AI technology into their organizations, which is being widely utilized in various areas such as data mining, industrial robotics, logistics, and human resource management. This technology has played a significant role in enhancing firms' production, operation, and management. However, AI technology is embedded in the interaction network within the organization (Beane, 2019; Sergeeva et al., 2020), which not only redefines the object of human resource management, but also shapes a new environmental structure in multiple dimensions, including supervision, incentive, and employee relationships (Xie et al., 2021). In our opinion, the application of AI technology may have a negative impact on employee responsibility.

The introduction of AI technology into organizations has transformed the object of management from just human employees to a complex system comprising intelligent robots and employees who are empowered by AI technology. The change in staff structure will erode the importance of high-incentive means, which focused on human psychological and emotional needs. AI enters organizations as an "employee" and automate many tasks. With the deepening of the application of AI technology, the number of "artificial intelligence staff" in the organization is increasing.

There are many differences between "artificial intelligence staff" and human staff. "Artificial intelligence staff" has the characteristics of automation and mechanization. Under the precise algorithm, "artificial intelligence staff" can work for a long time and with high efficiency (Złotowski et al., 2017), greatly reducing the need for manual supervision and high incentives. Standardized, procedural and scientific management methods are more appropriate for "artificial intelligence staff" (Xu and Xu, 2020).

In this context, the relevance of management principles and methods advocated by behavioral science theory has greatly diminished, and the "people-oriented" management philosophy has been greatly impacted. The significance of management approaches that prioritize taking responsibility, enhancing humanistic care, and establishing long-term stable relationships with employees within the organization has been reduced.

The relationship between managers and employees is another type of principal-agent relationship (Chen and Jiang, 2002; Anderson and Oliver, 1987; Banker et al., 1996; Deckop et al., 1999; Eisenhardt, 1988). To alleviate or solve the problems caused by principal-agent, firms usually establish incentive and supervision mechanisms to align the agent's behavior with the principal's interests (Fong and Tosi, 2007). Due to information asymmetry, external supervision can help reduce the deviation of agent behavior. However, when the cost of supervision is prohibitively high or the task of supervision is too complex, the effectiveness of the supervision mechanism in mitigating agency problems may be severely limited.

Employee responsibility is an important incentive mechanism that generates both extrinsic and intrinsic incentives for employees (Skudiene and Auruskeviciene, 2012). Numerous previous studies have shown that corporate social responsibility related to employees, which contributes to establishing a mutually beneficial relationship between the firm and its employees (Brammer et al., 2007; Skudiene and Auruskeviciene, 2012; Chun, 2009; Gharleghi et al., 2018), has a positive impact on employee outcomes such as innovation and labor productivity (Jones, 1995; Chun, 2009; Liu et al., 2020; Wu and Zhang, 2021; Gharleghi et al., 2018). Employee responsibility can be an effective incentive mechanism to address the agency problem and promote the agent's behavior to align with the interests of the principal.

During human-AI cooperation, production and monitoring occur simultaneously, such as in the case of instant delivery. AI allocates orders and optimizes distribution routes to promote on-time delivery and ensure a positive user experience. AI also records, tracks, monitors, evaluates, and provides feedback on the work of delivery staff. The application of AI technology not only provides strong data support for decision-making but also significantly improves labor efficiency and reduces supervision costs (Tong et al., 2021), potentially changing how firms address agency problems. With AI, managers can easily obtain a large amount of information about employees at a lower cost, making comprehensive and immediate employee supervision possible. As a result, when the cost of supervision decreases, firms may be less motivated to incentivize employees, which could reduce their willingness to take on employee responsibilities.

Although AI offers many benefits, its application in the workplace may have negative effects on human autonomy, privacy, and fundamental rights and freedoms (Aizenberg and van den Hoven, 2020; Schlund and Zitek, 2021; Rodrigues, 2020; Coglianese and Lehr, 2019; Köchling and Wehner, 2020; Todolí-Signes, 2019; Kim and Bodie, 2021). The extensive use of AI usually involves the collection and analysis of large amounts of data, most of which come from employees, thereby putting their privacy at risk. This large-scale data collection also creates new power that employers can use to manage and control employees. Some firms have even allowed AI to replace human resource managers in making legally effective decisions, such as recruitment and dismissal (Kim and Bodie, 2021; Köchling and Wehner, 2020; Todolí-Signes, 2019). For instance, in April 2019, Amazon was exposed for using artificial intelligence to monitor the work efficiency of warehouse workers, with employees failing to meet the productivity index being automatically dismissed[1]. When AI systems make decisions involving important employment impacts without transparency or accountability, employees may feel powerless and alienated (Kim and Bodie, 2021), resulting in potential violations of employees' rights. Therefore, we propose the following hypothesis:

H1: AI technology application is negatively related to a firm's employee responsibility.

The moderating effects

Product market competition. A firm in an industry can be subject to attacks from competitors, but it can also proactively launch attacks on other firms (Chen and Wang, 2015). With the increase in product market competition, managers have a stronger motivation to adopt certain offensive or defensive competition strategies to obtain or maintain competitive advantage. However, the reaction or strategies of competitors may bring many unexpected new problems to the firm or put the firm in a dilemma. The effect of competitive strategy will also be restricted by the reaction or strategy of many other competitors in the industry. As a result, the depth and breadth of the effect of a competitive strategy on the firm become highly uncertain. In contrast, when the level of competition in the product market is low, market uncertainty decreases, and the accuracy of probability estimation based on scenarios improves (Chen and Wang, 2015).

When industries face high levels of competition, organizations may encounter new situations and uncertainties (Ghosal and Loungani, 1996). Relying solely on "artificial intelligence employees" may not always be sufficient to address such challenges. It is, therefore, necessary to stimulate employee motivation, which plays a key role in sustaining a competitive advantage (Becker et al., 1996; Paul and Anantharaman, 2003). By supporting and developing the skills and motivation of employees, productivity, creativity, and discretion can be enhanced, leading to improved performance, profits, and growth (Becker and Gerhart, 1996).

In the face of new challenges and uncertainties brought about by product market competition, although AI has the potential to replace or augment humans in various activities, and can use big-data analysis, computational power, and machine learning technologies to help firms cope with competition, such as efficiently collecting information, generating new ideas through probability and statistical methods, identifying the correlation between variables, etc. (Agrawal et al., 2018; Kaplan and Haenlein, 2019; Haefner et al., 2021), its current state of development shows that in practice it tends to be limited to relatively narrow domains which require a significant level of human planning (Cockburn et al., 2019). Sample selection is a crucial aspect of model building in machine learning. Samples may consist of labels or historical data, and these labels may contain errors or impurities (Wu and Shang, 2020). When the real world changes rapidly, relying solely on historical data to make decisions can be extremely risky (Klotz, 2019), and predictions based on historical data may be distorted (Wu and Shang, 2020).

In the digital economy era, product service and customer experience are critical trends. Providing personalized products and services require firms to excel in creativity and emotion-based task. To gain a competitive advantage in the market, managers need to encourage employees to perform well in these types of tasks. While companies can leverage AI technology to reduce costs and pursue low-cost strategies by automating certain activities and streamlining their value chains, relying solely on low-cost strategies can make it easier for competitors to replicate them, and may not necessarily result in a sustainable competitive advantage (Islami et al., 2020). Currently, AI could potentially perform tasks based on big-data and lower the cost of labor-intensive tasks but cannot perform emotion-based tasks rely on human understanding and experience (Bakpayev et al., 2022). While AI can be an enabler of innovation, the prospect of AI replacing humans in creative tasks in the innovation process is still a distant goal (Truong and Papagiannidis, 2022). Therefore, we propose the following hypothesis:

H2: The negative relationship between AI technology application and employee responsibility weakens as the level of product market competition in which the firm operates increases.

Government ownership. There are significant differences between government-controlled firms and non-government-owned, or privately controlled firms, in terms of business objectives, corporate governance, and resource constraints. Government-controlled firms not only pursue the maximization of economic profits, but also undertake many responsibilities, such as expanding employment, supporting the construction of national public facilities, and maintaining social stability (Bai et al., 2006). Government-controlled firms can obtain more secure property and greater contractual rights through their closer ties with the government, which may lead managers in government-controlled firms to have insufficient innovation incentives (Freund, 2001; Ramamurti, 2000). Many managers of government-controlled firms are appointed by politicians (Qian, 1996; Ramaswamy, 2001). When making strategic decisions, they tend to prioritize political or social goals to increase their chances of being elected (Khwaja and Mian, 2005).

However, managers in the privately controlled firms often have more incentives to pursue market-driven and face more uncertainty than government-controlled firms. Managers have a stronger incentive to engage in efficiency-based innovative activities to gain long-term competitiveness (Gupta, 2005). Therefore, compared to government-controlled firms, privately controlled firms have more irregular creative tasks, that is, they adopt "new" methods in process, resulting in "new" outcomes, or engage in decision-making or behavior to deal with "uncertainty". Privately controlled firms pay more attention to innovation and have more irregular tasks within the organization than government-controlled firms.

The application of artificial intelligence technology can replace a human employee when the process can be made independent and is repeated with certain regularity (Wisskirchen et al., 2017). Even with the development of AI technology, the scope of replacement will continue to expand, but AI replacing humans in creative tasks in the innovation process remains a distant goal (Truong and Papagiannidis, 2022). Compared to government-controlled firms, the greater number of creative and irregular tasks in privately controlled firms will weaken the influence of artificial intelligence technology on employee replacement and management approaches. Therefore, we propose the following hypothesis:

H3: The negative relationship between the application of AI technology and employee responsibility is stronger for government-controlled firms than for privately controlled firms.

As illustrated in Fig. 1, it provides the research framework for our study.

Methods

Sample and data. Our sample comprised Chinese manufacturing firms listed on either the Shenzhen or Shanghai stock exchange

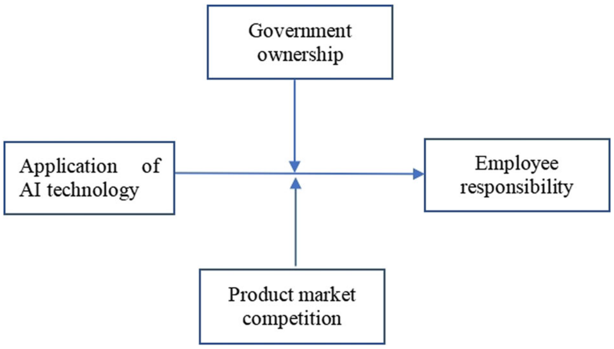

Fig. 1 Research framework. This Figure encompasses four primary variables: AI technology application, Employee responsibility, Government ownership, and Product market competition. AI technology application acts as the explanatory variable, while Government ownership and Product market competition function as moderating variables. Employee responsibility serves as the dependent variable within this framework.

between 2011 and 2020. We chose manufacturing firms as the research object for the following reasons: First, there were significant differences between different industries in terms of employee structure, application level of AI technology, etc. To ensure the comparability of industry background and better exclude the impact of industry background differences on the research conclusions, this study selected the manufacturing industry and sets the industry dummy variable with a two-digit code after C by referring to the China Securities Regulatory Commission (CSRC) Industry Classification Code. There were 30 Level-2 industries (codes) under C. Second, China was a large manufacturing country. The manufacturing industry was the most important pillar industry of China's national economy, the core of China's national economy, and the driving force of industrialization. The manufacturing industry had made a huge contribution to GDP, and among all listed companies, the proportion of listed companies belonging to the manufacturing industry was large. Manufacturing firms also had the characteristics of earlier listing, stable market performance, and more comprehensive financial data disclosure.

Our data came from two sources. The main source was a leading database in China—the China Stock Market & Accounting Research (CSMAR). The CSMAR was developed by GTA, a leading global provider of Chinese financial market data (Gao and Yang, 2016; Wang and Qian, 2011). However, the CSMAR database did not include the variable of employee responsibility. We adopted the employee responsibility index from HeXun.com (www.hexun.com) as the measure for the employee responsibility variable in this study. HeXun.com provided CSR indices for China's listed firms, covering five main dimensions: shareholder responsibility, employee responsibility, responsibility for suppliers, customers, and consumer rights, environmental responsibility, and social responsibility. These indices were based on publicly disclosed firm annual reports and CSR disclosures. We selected the period of 2011–2020 for this study to ensure consistency in measurement criteria and data availability. After merging the two databases and removing observations with missing key explanatory variables, the final unbalanced panel sample contained 2395 firms.

Measures

Dependent variable. Corporate employee responsibility (ER). The dependent variable was employee responsibility. Following the methods of previous research on the CSR of China's listed firms (Gong et al., 2021; Li et al., 2022), we used employee responsibility score from HeXun.com as an indicator of the firm's employee responsibility. HeXun.com provided employee responsibility indices of China's listed firms for three major dimensions: performance responsibility (per capita income of employees), safety responsibility (safety inspection, safety training), and care responsibility (employee caring consciousness, list of members of caring for employees, consolation money for employees).

Explanatory variable. To test the hypotheses, the variable "AI technology application" needed be highly condensed. This kind of information was more likely to be reflected in the annual report of the firm with a summary and guidance. The usage of words in the annual report could reflect the firm's strategy and prospects, and to a large extent, represent the management idea respected by the firm and the development path under the guidance of this management idea.

The application of AI technology was the core explanatory variable of our research, representing the extent to which a company used AI technology to promote the improvement of its internal production, operation, or management. The application of artificial intelligence technology reflected a company's level of engagement in the application of AI technology. At the time, there was limited research on quantitative measurements of AI technology application intensity. As AI technology application represented a company-wide strategic change that involves a wide range, it was difficult to decompose and quantify technically. Drawing on the measurement methods of other behavioral variables in strategic management research (Cho and Hambrick, 2006; Eggers and Kaplan, 2009; Nadkarni and Barr, 2008; Guo and Xu, 2021; Wu et al., 2021), we attempted to indirectly measure the application of AI technology through text analysis of the annual reports of listed companies.

The annual report of a listed company was an official document that disclosed the company's financial status and operating results in a fiscal year. It covered not only financial indicators but also strategic options. If the company had made significant strategic changes, these changes would be described in the annual report. As the annual reports of listed companies were public and of great significance, the company was more rigorous in the disclosure of annual reports. In the field of strategic management, there were many measures of management behavior based on annual report text analysis, such as management perception based on the frequency, tone and readability (Cho and Hambrick, 2006; Eggers and Kaplan, 2009; Nadkarni and Barr, 2008). The application of artificial intelligence technology was an important strategic choice in the digital and intelligent era, and relevant information should have been included in the annual report. As intelligent manufacturing became an inevitable choice for manufacturing enterprises (Guo and Xu, 2021), companies had an incentive to disclose their actions in their annual reports. Therefore, it was reasonable and feasible to mine information about the application intensity of artificial intelligence technology from the annual reports of listed companies.

The frequency with which terms appeared in annual reports indicated their relative importance (Unerman, 2000). The word frequency method was the best choice for quantitative measurement based on large sample text (Roberts, 1997). The firm's AI technology application intensity variable could also be measured by word frequency. Guided by this idea and following previous studies (Guo and Xu, 2021; Wu et al., 2021), we used the keyword frequency method to quantitatively measure the application intensity of the firm's AI technology. This method was effective on the premise of accurately screening the feature words of artificial intelligence technology application in the annual report (Guo and Xu, 2021).

Firms were using AI as a virtual labor force to enter the enterprise as an "employee". The way in which "artificial intelligence employees" collaborated with human employees to transform and improve the original technical system and production system. An "AI employee" working in a specific role required the ability to perform certain tasks, which depended on the layout and development of key core technologies of artificial intelligence. Modern artificial intelligence had four key capabilities: perception, comprehension, action and learning (Bawack et al., 2021).

We collected and organized annual reports of Chinese manufacturing firms listed on either the Shenzhen or Shanghai stock exchange through Python crawler function, extracted all the contents through JavaPDFbox library, and used this as the subsequent keyword screening data pool. Referring to previous research (Bawack et al., 2021; Wu et al., 2021; Liu et al., 2022) and important policy documents on AI technology development and digital transformation, we summarized and extracted keywords related to the four key capabilities of AI (perception, comprehension, action, and learning) mentioned above. The following is a list of AI keywords extracted from the sample company annual reports: artificial intelligence, business intelligence, image understanding, investment decision aids, intelligent robotics, machine learning, deep learning, semantic search, biometrics, face recognition, speech recognition, authentication, autonomous driving, natural language processing.

On this basis, we excluded expressions of negative words such as "no" before the keywords and "artificial intelligence" keywords that did not belong to the company (including the company's shareholders, customers, suppliers, and company executives' profiles). Based on the data pool formed by the text extraction of the annual report of listed firms using Python, we searched, matched, and performed word frequency counts according to the keywords. Next, we classified and aggregated the word frequency of key technical capabilities to form the final total word frequency, constructing the index system of the application intensity of the firm's artificial intelligence technology. The correlation analysis of word frequency showed that the words were highly correlated, with most of them significantly correlated with "artificial intelligence" at a significance level of $p < 0.01$. We took the natural logarithm of the total word frequency to deal with the "right deviation" feature of the data. In the robustness test, we set this variable as a dummy variable. When the total word frequency of "artificial intelligence technology" keywords was greater than or equal to 1, it was set to 1, and the others were set to 0.

Moderating variables. Product market competition (HHI). We used Herfindahl index as an indicator of product market competition. The index is expressed by the sum of squares of the ratio of sales of specific companies to sales of all companies in the industry, as show in formula (1).

$$HHI = \sum_{i=1}^{N}(X_i/X) = \sum_{i=1}^{N} S_i^2 \tag{1}$$

X_i is the sales volume of the ith company, X is the sales volume of all companies in the industry, S_i is the market share of the ith company, and N is the number of companies in the industry. When the Herfindahl index is high, it indicates a low level of market competition, while a low Herfindahl index suggests a highly competitive market.

Government ownership (SOE). SOE was set as a dummy variable. If the ultimate owner of a firm is the Chinese government and its agencies, the variable is 1, and for others, it is 0 (Wang and Qian, 2011).

Control variables. We included the following control variables, following previous research on corporate social responsibility (Hong et al., 2016; Xu and Liu, 2017; Padgett and Galan, 2010; Huang et al., (2019); Zhang et al., 2018; Cao et al., 2015):①firm characteristics, including firm size (SZ), firm age (FA), asset-liability ratio (LEV), firm profitability (ROA), firm diversification (DH), and R&D expenditure ratio (RD); and ②corporate governance variables, including ownership concentration (FS), board size (BZ), CEO duality (DUA), executive shareholding ratio (RM), independent director ratio (IND), TMT functional heterogeneity (DOM), age diversity (DAG), tenure diversity (DTE), average age (AG), average tenure (TE), education average (EU), educational diversity (DEU) and percentage of females (FE). Following the methods of previous research (Carpenter and Fredrickson, 2001), we used formula (2) to measure the functional heterogeneity of TMT.

$$DOM = 1 - \sum S_i^2 \tag{2}$$

S_i refers to the proportion of the number of people with ith functions in the total number of TMT, and its value is between 0 and 1. The closer it is to 1, the higher the degree of functional heterogeneity of TMT, and the closer it is to 0, the lower the degree of functional heterogeneity of TMT. In this study, the educational background of TMT was assigned as follows: 6 years for primary school, 9 years for junior middle school, 12 years for senior high school and technical secondary school, 16 years for bachelor's degree, 19 years for master's degree and 22 years for doctoral degree. The average education was measured by taking the average education years of TMT. Following the research of Berry (1971), we used the diversification index to measure firm diversification, as shown in formula (3).

$$DH = \sum P_i^2 \tag{3}$$

P_i represents the proportion of the ith industry in the total income. A higher *DH* value indicates lower diversification. Table 1 provided the definitions of the main variables used in this study.

Model setting. The following equation was used to test the hypotheses:

$$\begin{aligned} ER = a + \beta_1 AI + \beta_2 AI \times \text{Moderators} + \beta_3 \text{Moderators} \\ + \beta_4' \sum C + \sum \text{industry} + \sum \text{year} + \varepsilon \end{aligned} \tag{4}$$

where ER was the dependent variable in model (4), representing the level of employee responsibility. AI was an independent variable, indicating the degree of application of AI technology in firms. Moderators included product market competition and government ownership. C was a set of control variables expected to influence employee responsibility. At the same time, this study also controlled the fixed effect of year and industry.

Results

We investigated whether there was a potential multicollinearity problem by computing the variance inflation factor (VIF). The mean VIF was about 2.07, below 10 for regression models (Ryan, 1997). Multicollinearity was not a significant issue in this study. To avoid possible problems of heteroscedasticity, sequence correlation, and autocorrelation in the panel data, we used the Driscoll-Kraay standard error (Driscoll and Kraay, 1998) to estimate fixed effects.

Descriptive statistics. Descriptive statistics and the correlation matrix were presented in Table 2. The results showed that the mean of ER was 2.22, with a standard deviation of 2.7, indicating significant differences in employee responsibility scores among various firms. The mean of AI was 0.22, with a standard deviation of 0.6, suggesting that artificial intelligence technology was extensively utilized in China's manufacturing listed firms and that the application degree of AI technology varied significantly across different firms. The correlation

Table 1 Definition of main variables.

Variable type	Variable symbol	Variable name	Measurement method
Dependent variable	ER	employee responsibility	See the article for details
Explanatory variable	AI	AI technology application	See the article for details
Moderating variables	SOE	government ownership	See the article for details
	HHI	product market competition	See the article for details
Control variables	FS	ownership concentration	The ratio of the number of shares held by the largest shareholder to the number of shares held by the second-largest shareholder
	AG	average age	The average of TMT age
	FE	percentage of females	The percentage of females within a TMT
	TE	average tenure	The average of TMT tenures
	BZ	board size	The natural logarithm of the number of board members
	IND	independent director ratio	Ratio of the number of independent directors to the number of board of directors
	DUA	CEO duality	CEO duality is set as a dummy variable, and if the situation where the same person serves simultaneously as CEO and chairperson of the board, the variable is 1 and others are 0
	DTE	tenure diversity	The standard deviation of tenure within the TMT divided by the average tenure of TMT
	DAG	age diversity	The standard deviation of age within the TMT divided by the average age of TMT members was measured
	EU	education average	See the article for details
	DEU	educational diversity	The standard deviation of education with the TMT divided by the average education of TMT
	DOM	TMT functional heterogeneity	See the article for details
	ROA	firm profitability	Net profit/total assets
	RM	executive shareholding ratio	Number of shares held by senior executives / total shares
	FA	firm age	The natural logarithm is used to measure the number of years obtained by subtracting the year of establishment of the sample company
	DH	firm diversification	See the article for details
	RD	R&D expenditure ratio	The ratio of R&D expenditure to total assets
	LEV	asset-liability ratio	The ratio of year-end liabilities to total assets at the end of the year
	SZ	firm size	The natural logarithm of the total assets at the end of the period

coefficient between ER and AI was −0.019, which was significant at the 1% level, aligning with expectations. This suggested that as the application intensity of AI technology increased, the level of employee responsibility decreased correspondingly. However, further testing was needed to confirm the results of H1. In the subsequent analysis, we controlled for other factors that might have affected ER and used regression analysis to further examine the relationship between the two variables.

Regression analysis results. Table 3 showed the regression analysis results of AI technology application on employee responsibility. Model (1) reported the effects of the basic control variables and moderating variables. Model (2) had the independent variable added. The results showed that AI was significantly negatively associated with ER (beta = −0.089, $p < 0.05$). These results supported H1. As shown in model (3), the interaction term between AI and HHI was negative and significant for ER (beta = −1.233, $p < 0.01$). The results supported H2. As shown in model (4), the interaction item between AI and SOE was negative and significant for ER (beta = −0.451, $p < 0.01$). These results supported H3. Models (5) was the full models, including all the interactions.

Robustness test

Endogenous problems. ①Lag one period. This study tested whether the application of AI technology would affect the level of employee responsibility, but it was also possible that firms with high level of employee motivation had a higher level of application of artificial intelligence technology. In other words, there might have been the endogenous problem of reverse causality in this study. To solve this problem, this study analyzed the explanatory variables after a one-period lag. Adding the letter "L" before the original variable symbol indicated a lag of one period. For example, "LAI" meant the variable "AI" with a one-period lag, "LHHI" meant the variable "HHI" with a one-period lag, and "LSOE" meant the variable "SOE" with a one-period lag. Table 4 showed the regression results after incorporating a one-period lag for the explanatory variables. The results of model (2)–(4) in Table 4 showed that LAI was significantly negatively associated with ER (beta = −0.099, $p < 0.1$). In model (3), the interaction term between LAI and LHHI was negative and significant for ER (beta = −0.799, $p < 0.05$). In model (4), the interaction term between LAI and LSOE was negative and significant for ER (beta = −0.511, $p < 0.01$). The results are consistent with the previous results.

②Propensity scores matching method. To address the problem of sample selection bias, this study used the propensity score matching method to test the robustness. The propensity score was calculated by logit or probit regression, and the samples were matched accordingly. Referring to the three-level industrial classification of manufacturing industry in the "industry classification structure and code of China Securities Regulatory Commission", we coded the application of artificial intelligence technology (AI_H). When the application of AI technology in

Table 2 Descriptive statistics and correlations.

	Mean	S.D.	1	2	3	4	5	6
1. ER	2.22	2.7	1					
2. AI	0.22	0.6	−0.019***	1				
3. HHI	0.27	0.07	−0.031***	0.075***	1			
4. SOE	0.27	0.45	0.202***	−0.068***	0.043***	1		
5. FS	8.03	13.2	0.088***	−0.061***	0.009	0.256***	1	
6. RM	0.09	0.15	−0.115***	0.065***	−0.055***	−0.340***	−0.141***	1
7. BZ	2.23	0.17	0.126***	−0.069***	0.028***	0.256***	0.022***	−0.154***
8. IND	0.38	0.05	−0.018**	0.043***	−0.032***	−0.065***	0.004	0.101***
9. DUA	0.32	0.47	−0.080***	0.066***	−0.020***	−0.292***	−0.094***	0.483***
10. DOM	0.46	0.21	0.046***	−0.044***	−0.025***	0.003	0.016**	0.068***
11. AG	47.1	3.67	0.039***	−0.014*	0.046***	0.288***	0.056***	−0.122***
12. DAG	0.13	0.05	−0.101***	−0.003	−0.005	−0.291***	−0.098***	0.138***
13. TE	3.75	1.47	0.047***	0.034***	0.001	0.080***	0.069***	−0.156***
14. DTE	0.63	0.26	0.057***	0.033***	0.012*	0.268***	0.086***	−0.295***
15. EU	16.95	1.26	0.118***	0.111***	−0.024***	0.180***	−0.003	−0.106***
16. DEU	0.1	0.04	−0.025***	0.006	−0.013	−0.107***	−0.075***	0.076***
17. FE	0.15	0.15	−0.086***	0.025***	−0.036***	−0.186***	−0.059***	0.091***
18. RD	0.02	0.02	0.022***	0.289***	0.013*	−0.120***	−0.083***	0.160***
19. LEV	0.39	0.2	0.102***	−0.009	0.106***	0.292***	0.139***	−0.251***
20. ROA	0.05	0.07	0.053***	−0.006	−0.054***	−0.132***	−0.070***	0.172***
21. DH	0.83	0.23	−0.027***	−0.029***	0.065***	−0.083***	−0.025***	0.094***
22. SZ	21.91	1.19	0.235***	0.077***	0.097***	0.329***	0.109***	−0.268***
23. FA	2.83	0.35	−0.046***	0.044***	0.054***	0.204***	0.056***	−0.179***
	7	**8**	**9**	**10**	**11**	**12**	**13**	**14**
8. IND	−0.568***	1						
9. DUA	−0.173***	0.108***	1					
10. DOM	0.051***	−0.041***	−0.016**	1				
11. AG	0.131***	−0.034***	−0.049***	−0.035***	1			
12. DAG	−0.106***	0.018**	0.124***	−0.009	−0.202***	1		
13. TE	0.066***	−0.027***	−0.065***	−0.075***	0.274***	−0.148***	1	
14. DTE	0.092***	−0.023***	−0.173***	−0.093***	0.071***	−0.053***	0.032***	1
15. EU	0.066***	0.019**	−0.036***	0.011	0.051***	−0.138***	0.031***	0.156***
16. DEU	−0.032***	0.006	0.055***	0.037***	0.007	0.105***	−0.061***	−0.035***
17. FE	−0.107***	0.052***	0.086***	−0.049***	−0.176***	0.154***	−0.048***	−0.027***
18. RD	−0.064***	0.021***	0.092***	0.087***	−0.025***	−0.026***	−0.01	−0.126***
19. LEV	0.137***	−0.014**	−0.131***	−0.065***	0.105***	−0.140***	0.080***	0.256***
20. ROA	−0.007	−0.015**	0.069***	0.054***	−0.035***	0.007	−0.065***	−0.257***
21. DH	−0.045***	0.024***	0.031***	0.043***	−0.061***	0.031***	−0.097***	−0.164***
22. SZ	0.238***	−0.018**	−0.168***	−0.035***	0.247***	−0.194***	0.233***	0.277***
23. FA	0.046***	−0.016**	−0.090***	−0.168***	0.266***	−0.045***	0.171***	0.243***
	15	**16**	**17**	**18**	**19**	**20**	**21**	**22**
16. DEU	0.080***	1						
17. FE	−0.038***	0.002	1					
18. RD	0.156***	0.019**	0.006	1				
19. LEV	0.106***	−0.068***	−0.136***	−0.147***	1			
20. ROA	−0.033***	0.048***	0.039***	0.162***	−0.393***	1		
21. DH	−0.068***	0.034***	0.005	0.134***	−0.142***	0.126***	1	
22. SZ	0.252***	−0.029***	−0.130***	−0.082***	0.451***	−0.033***	−0.155***	1
23. FA	0.059***	−0.059***	0.01	−0.044***	0.157***	−0.087***	−0.108***	0.170***

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

firms was higher than the average value for specific years and industries, it was set as 1, which was defined as the experimental group; otherwise, it was 0, which was defined as the control group. The following Eq. (5) was set:

$$Pr(AI\_H) = \beta_0 + \beta_1 SOE + \beta_2 HHI + \beta_3 FS + \beta_4 RM + \beta_5 BZ + \beta_6 IND + \beta_7 DUA + \beta_8 DOM + \beta_9 AG + \beta_{10} TE + \beta_{11} DTE + \beta_{12} EU + \beta_{13} DEU + \beta_{14} FE + \beta_{15} RD + \beta_{16} LEV + \beta_{17} ROA + \beta_{18} DH + \beta_{19} SZ + \beta_{20} FA + \beta_{21} DAG + \sum_{industry} + \sum_{year} + \varepsilon \tag{5}$$

The propensity score was calculated by logit regression, and other variables were consistent with the above. Table 5 showed the regression results after one-to-one nearest neighbor matching, (2)–(4) showed AI and AI × SOE, AI × HHI on employee responsibility were basically consistent with previous findings. In addition, core matching, radius matching, and kernel matching were also selected in this study, and the regression results were generally consistent with the previous results.

Alternative measure of AI technology application. In this study, the method of Wang and Du (2021) was used for measurement, and the application of AI technology was set as a dummy variable (AI_D). If the number of relevant expressions of artificial intelligence technology in the current report was greater than or equal to 1, then AI_ D was assigned as 1, and others were set to 0. Table 6

Table 3 Regression analysis results of AI technology application on employee responsibility.

	(1)	(2)	(3)	(4)	(5)
AI		−0.089**	−0.084**	−0.011	−0.012
		[0.018]	[0.012]	[0.724]	[0.708]
AI × HHI			−1.233***		−0.867***
			[0.004]		[0.006]
AI × SOE				−0.451***	−0.426***
				[0.000]	[0.000]
HHI	−0.206	−0.108	−0.120	−0.041	−0.053
	[0.202]	[0.536]	[0.651]	[0.814]	[0.823]
SOE	0.007	0.008	0.018	0.053	0.058
	[0.912]	[0.897]	[0.780]	[0.626]	[0.589]
Intercept	−13.630***	−13.961***	−14.061***	−13.962***	−14.033***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Control variables	Control	Control	Control	Control	Control
Industry	Control	Control	Control	Control	Control
Year	Control	Control	Control	Control	Control
R^2	0.1244	0.1247	0.1251	0.1262	0.1263
F	326.660	325.278	315.922	303.194	44.577
N	14,267	14,267	14,267	14,267	14,267

Continuous variables were tailed at 1% level, p-value in brackets, ***$p < 0.01$, **$p < 0.05$. The same below.

Table 4 Regression results with explanatory variables lagged by one period.

	(1)	(2)	(3)	(4)	(5)
LAI		−0.099*	−0.096*	−0.013	−0.013
		[0.078]	[0.079]	[0.686]	[0.678]
LAI × LHHI			−0.799**		−0.367**
			[0.018]		[0.044]
LAI × LSOE				−0.511***	−0.499***
				[0.005]	[0.005]
LHHI	0.004	0.111	0.099	0.184	0.177
	[0.992]	[0.803]	[0.811]	[0.684]	[0.684]
LSOE	0.100	0.103	0.112	0.161	0.164
	[0.363]	[0.346]	[0.311]	[0.317]	[0.305]
Intercept	−7.598**	−7.969**	−8.018**	−7.983**	−8.005**
	[0.025]	[0.019]	[0.018]	[0.019]	[0.019]
Control variables	control	control	control	control	control
Industry	control	control	control	control	control
Year	control	control	control	control	control
R^2	0.1280	0.1284	0.1285	0.1302	0.1303
F	32.402	19.947	17.912	21.064	24.826
N	13,552	13,552	13,552	13,552	13,552

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

showed the regression results after replacing the variable of AI technology application measurement. In model (1), AI_D was significantly negatively associated with ER (beta = −0.165, $p < 0.01$). In model (2), the interaction term between AI_ D and HHI was negative and significant for ER (beta = −1.128, $p < 0.1$). In model (3), the interaction term between AI_ D and SOE was significantly negatively associated with ER (beta = −0.756, $p < 0.01$). The results were consistent with the previous findings.

Alternative measure of product market competition. In this study, based on the research of Tan (2017), the Herfindahl index of enterprise assets (HHI_A) was used for measurement, as seen in formula (6).

$$\mathrm{HHI\_A} = \sum_{i=1}^{N} \left(A_i / A\right) \tag{6}$$

A_i is the total assets of the ith company, X represents the total assets of all companies in the industry, and N represents the number of companies in the industry. The larger the HHI_A, the less competitive the market was. Table 7 showed the regression results after replacing the variable of product market competition measurement. In model (2), AI was significantly negatively associated with ER (beta = −0.091, $p < 0.05$). In model (3), the interaction item between AI and HHI_A was negative and significant for ER (beta = −1.1660, $p < 0.05$). In model (4), The interaction item between AI and SOE was negative and significant for ER (beta = −0.453, $p < 0.01$). The results were consistent with the previous results.

Further analyses

Mediating effect of supervision cost. Due to the information asymmetry and incomplete contract, there are agency problems between principal and agent. Effective incentive and supervision are two important ways to solve the agency problem (Fong and Tosi, 2007). Although external supervision can reduce the deviation of agent behavior, when the cost of supervising is too

Table 5 One to one nearest neighbor matching.

	(1)	(2)	(3)	(4)	(5)
AI		−0.124**	−0.122**	0.001	−0.003
		[0.032]	[0.039]	[0.985]	[0.942]
AI × HHI			−1.498***		−1.042***
			[0.005]		[0.008]
AI × SOE				−0.637***	−0.609***
				[0.001]	[0.001]
HHI	−0.044	0.070	0.159	0.164	0.222
	[0.934]	[0.899]	[0.723]	[0.762]	[0.631]
SOE	0.066	0.057	0.072	0.204	0.208
	[0.573]	[0.622]	[0.517]	[0.273]	[0.254]
Intercept	−17.349***	−17.787***	−18.040***	−17.753***	−17.931***
	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]
Control variables	Control	Control	Control	Control	Control
Industry	Control	Control	Control	Control	Control
Year	Control	Control	Control	Control	Control
R^2	0.1491	0.1497	0.1504	0.1532	0.1535
F	15.322	48.342	18.336	14.689	16.453
N	6404	6404	6404	6404	6404

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

Table 6 Alternative measure of AI technology application of firms.

	(1)	(2)	(3)	(4)
AI_D	−0.165***	−0.166***	−0.031	−0.034
	[0.000]	[0.000]	[0.217]	[0.210]
AI_D × HHI		−1.128*		−0.775
		[0.092]		[0.197]
AI_D × SOE			−0.756***	−0.743***
			[0.000]	[0.000]
HHI	−0.123	0.051	−0.036	0.082
	[0.443]	[0.802]	[0.816]	[0.676]
SOE	0.012	0.015	0.170	0.169*
	[0.844]	[0.809]	[0.103]	[0.099]
Intercept	−13.980***	−14.090***	−13.871***	−13.948***
	[0.001]	[0.001]	[0.001]	[0.001]
Control variables	Control	Control	Control	Control
Industry	Control	Control	Control	Control
Year	Control	Control	Control	Control
R^2	0.1249	0.1250	0.1267	0.1268
F	319.981	461.353	234.155	190.294
N	14,267	14,267	14,267	14,267

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

high or supervision is too difficult, the role of supervision mechanism in eliminating agency problem is very limited. It is essentially unrealistic for the principal to understand the agent's work behavior and attitude in real-time without the use of advanced technology.

Firms can design a set of incentive mechanism to reduce agency costs. Becker (1974) proposed that if the householder has a sufficient level of altruistic behavior toward family members, then the beneficiary family members will care for the householder and other family members, regardless of how selfish they are. Similar to the reaction of family members to the householder's altruistic behavior, altruistic behavior in firms is inversely proportional to agency cost, and there is a substitution relationship between the two (Wang et al., 2014; Davis et al., 1997). Employee responsibility generates extrinsic and intrinsic incentives for employees (Skudiene and Auruskeviciene, 2012). Although the interests between managers and employees are not exactly the same (Chen and Jiang, 2002), if the managers care about employees and take on higher level of employee responsibilities, it is conducive to cultivate employees' loyalty and trust in managers (Brammer et al., 2007; Skudiene and Auruskeviciene, 2012; Chun, 2009; Gharleghi et al., 2018), and employees will spontaneously eliminate a series of opportunistic behaviors. When it is difficult to supervise agents or the cost of supervising agents is high, the motivation of firms to reduce agency costs through incentives will continue to increase (Chen and Jiang, 2002). We think that high supervision cost will increase the tendency of firms to adopt incentive method to reduce agency costs.

With the extensive application of artificial intelligence technology in organization production, operation, and management, in the process of human-AI cooperation, AI application can track employees' activities at work, more accurately grasp and analyze a large amount of information about employees' activities and behaviors (Tong et al., 2021). However, these activities were previously primarily the responsibility of managers, which required managers to monitor the workplace (Mintzberg, 1989). Now, with the help of AI, Managers could master a large amount of information about employees at a small cost, and the principal could directly supervise the agent, reducing the information asymmetry between the principal and the agent and eliminating the agency problem. We think that the supervision cost mediated the effect of AI on employee responsibility. Figure 2 displayed the research framework of the mediation effect of supervision cost.

Much previous research used the management expense ratio to measure the supervision cost, guarantee cost and the cost caused by excessive on-the-job consumption of managers (Ang et al., 2000; Wang et al., 2014). management expense were the expenses incurred by the administrative departments of firms to organize and manage the production and operation activities of employees. Because the number of employees in each company is different, this study took the natural logarithm of the ratio of management expenses to the number of employees as the measurement index of supervision cost (MC). Table 8 showed the results of the mediating effect of supervision cost. Model (1) results showed that AI and ER had a significantly negative relationship (beta = −0.089, $p < 0.05$), and model (2) showed that AI had a significantly negative effect on MC (beta = −0.034, $p < 0.05$), which indicates that AI technology can indeed reduce supervision

Table 7 Alternative measure of product market competition.

	(1)	(2)	(3)	(4)	(5)
AI		−0.091**	−0.092**	−0.012	−0.016
		[0.015]	[0.016]	[0.693]	[0.615]
AI × HHI_A			−1.660**		−1.087
			[0.044]		[0.143]
AI × SOE				−0.453***	−0.437***
				[0.000]	[0.000]
HHI_A	0.535	0.577	0.374	0.630	0.495
	[0.291]	[0.251]	[0.431]	[0.199]	[0.295]
SOE	0.006	0.008	0.005	0.054	0.050
	[0.926]	[0.902]	[0.933]	[0.623]	[0.631]
Intercept	−13.844***	−14.162***	−14.151***	−14.157***	−14.150***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Control variables	Control	Control	Control	Control	Control
Industry	Control	Control	Control	Control	Control
Year	Control	Control	Control	Control	Control
R^2	0.1244	0.1248	0.1250	0.1262	0.1263
F	29.470	29.511	29.272	41.271	26.546
N	14,267	14,267	14,267	14,267	14,267

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

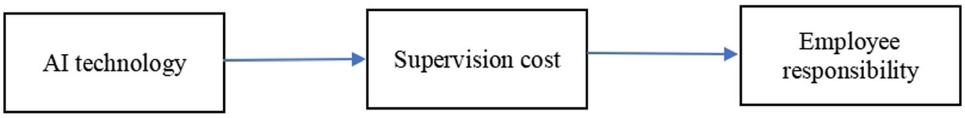

Fig. 2 Mediating effect. This Figure examines the mediating effect of Supervision cost between the AI technology application and Employee responsibility.

cost. In model (3), both AI and MC were included, and the results showed that AI had a significantly negatively effect on ER (beta = −0.067, $p < 0.05$), while MC had a significantly positive effect on ER (beta = 0.656, $p < 0.01$). In this study, the Sobel test was carried out. The Z statistic was −4.392 and was significant at the level of 1%. The results indicate that the supervision cost partially mediates the relationship between the application of artificial intelligence technology and employee responsibility.

Further study. In the previous sections, we found that the application of artificial intelligence technology could reduce the level of employees' responsibility. Moreover, in the practice of human resource management, many negative reactions of employees caused by the application of artificial intelligence technology, such as increased turnover intention and reduced work motivation (Li et al., 2019; Bhargava et al., 2021; Chui et al., 2015; Brougham and Haar, 2018), to a certain extent, reflect that there is no collaborative relationship between AI technology and employees in many firms. However, if artificial intelligence technology is widely used in firms, it can improve labor productivity. Does it mean that in the era of artificial intelligence, "people-oriented" principle and "social people" as the center of management idea are outdated? In order to test the above problems, we try to compare the effects of artificial intelligence technology and employee responsibility on firm productivity and innovation performance. According to the theory of behavior science, taking responsibilities will form a relationship of mutual trust and cooperation with their employees (Brammer et al.,2007; Skudiene and Auruskeviciene, 2012; Chun, 2009; Gharleghi et al., 2018).

A high level of employee responsibility will affect the initiative (Skudiene and Auruskeviciene, 2012), motivate people to choose the company as employees (Heslin and Ochoa, 2008), and enhance the satisfaction, commitment and loyalty of employees (Aguilera et al., 2007; Heslin and Ochoa, 2008). This will not only improve production efficiency but also make employees more willing to participate in innovative activities (Wu and Zhang,2021). In addition, firms with a high level of employee responsibility have a more harmonious and relaxed working environment, which is conducive to internal communication and knowledge sharing, and improve innovation performance (Harrison et al., 2010; Wu and Zhang, 2021).

In the previous analysis, we have seen the significant role of AI technology, which can improve labor efficiency through automated production and automated management (Agrawal et al., 2019a; Agrawal et al., 2019b; Cockburn et al., 2019; Tong et al., 2021). At the same time, the use of these technologies reduces the incentive for companies to take on employee responsibilities. Previous studies have shown that many human employees have negative perceptions of "AI employees" entering the company to engage in production and management (Li et al., 2019; Bhargava et al., 2021; Chui et al., 2015; Brougham and Haar, 2018). For example, they are afraid of being replaced by AI technology and think that AI's tracking and monitoring at work may infringe on their privacy (Raveendhran and Fast, 2019), etc. The strict monitoring, impersonal, and automated management system may not only make employees subject to discriminatory, invasive, or other unfair treatment (Kim and Bodie, 2021) but also bring artificial distance between organizations and employees (Stone et al., 2015). Human resource management practices have become more transaction-oriented than relation-oriented (Stone et al., 2015).

These negative effects will damage the relationship between firms and employees, and harm employees' performance (Tong et al., 2021). Over-reliance on automation tends to lead to the loss of individual skills and path dependence in an organization, subjecting the organization and employees to given machine operations and processes. Moreover, although AI can be an innovation enabler, it is still a distant goal for AI to completely replace human beings and complete creative tasks in the innovation process (Truong and Papagiannidis, 2022).

We think that the use of AI technology can improve production efficiency due to automated production and automated management, but it may not have a significant positive impact on innovation performance. However, employee responsibility not only improves production efficiency but also has a significant positive impact on innovation performance. Figure 3 displayed the research framework comparing the effects of the AI technology application and employee responsibility on production efficiency and innovation performance.

We measured the production efficiency of firms by the total factor productivity of firms. Total factor productivity of firms was estimated using the Ordinary Least Squares method (EOLS), Orthogonal Projection method (EOP), and Linear Programming method (ELP) (Kasahara, Rodrigue, 2008; Dai et al., 2017; Zhang, Liu, 2017). We measured the innovation performance of firms from the two dimensions: output of innovation (PA) and innovation efficiency (PE). Following the research of Kong et al. (2017), the output of innovation was measured as the natural logarithm of the number of patents application by a firm in a given year. Innovation efficiency was measured by the ratio of innovation output to R&D investment. R&D investment was measured as the natural log of the R&D expenditure. Table 9 showed the results of effects of AI Technology application and employee responsibility on production efficiency and innovation performance. The test results of models (1)–(3) showed that there was a significant positive relationship between ER and production efficiency (beta11 = 0.004, $p < 0.05$; beta12 = 0.004, $p < 0.05$; beta13 = 0.005, $p < 0.01$), and a positive relationship between AI and production efficiency (beta21 = 0.014, $p < 0.05$; beta22 = 0.009, $p < 0.1$; beta23 = 0.011, $p < 0.05$). The results of model (4) showed that there was a significant positive relationship between ER and innovation output (PA) (beta = 0.019, $p < 0.05$), while there was no significant relationship between AI and innovation performance. The results of model (5) showed that there was a significant positive relationship between ER and innovation efficiency (PE) (beta = 0.001, $p < 0.05$), while the relationship between AI technology application (AI) and innovation efficiency (PE) was not significant.

Table 8 The mediating role of supervision cost.

	ER	MC	ER
	(1)	(2)	(3)
AI	−0.089**	−0.034**	−0.067**
	[0.018]	[0.047]	[0.040]
MC			0.656***
			[0.000]
HHI	−0.108	−0.451*	0.229
	[0.536]	[0.086]	[0.372]
SOE	0.008	−0.052**	0.043
	[0.897]	[0.017]	[0.488]
Intercept	−13.961***	11.114***	−21.256***
	[0.001]	[0.000]	[0.000]
Control variables	Control	Control	Control
Industry	Control	Control	Control
Year	Control	Control	Control
R^2	0.1247	0.2100	0.1340
F	325.278	137.582	403.170
N	14,267	14,306	14,262

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

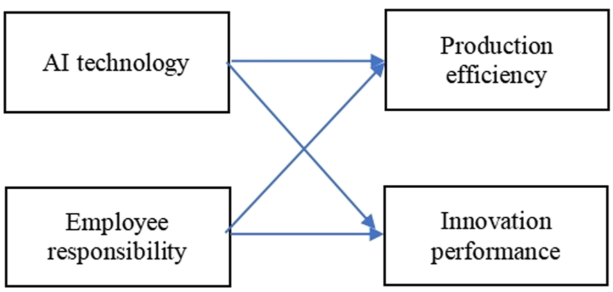

Fig. 3 Comparison of influence effects. This Figure examines the effects of the AI technology application and Employee responsibility on Production efficiency and Innovation performance. Innovation performance encompasses both Innovation output and Innovation efficiency.

Discussion and conclusions

Many scholars have explored the impact of artificial intelligence technology in the workplace on economic outcomes such as employment, income distribution, and productivity (Frey and Osborne, 2017; Daugherty and Wilson, 2018; Agrawal et al., 2019a; Agrawal et al., 2019b; Cockburn et al., 2019; Gries, Naudé (2018); Gordon, 2016, 2018; Jones, 2009), and have obtained rich and valuable research results, deepening the knowledge and understanding of related fields. However, these studies mainly focus on economic performance, and many research conclusions are based on industry-level data or theoretical model predictions. There are relatively few empirical studies on social performance based on firm-level data.

In addition, when using firm-level data to study the impact of artificial intelligence technology in the workplace, more negative conclusions were drawn, such as reducing employees' job satisfaction, organizational commitment and increasing turnover intention (Li et al., 2019; Bhargava et al., 2021; Chui et al., 2015; Brougham and Haar, 2018). These findings have primarily been based on employees' perceptions and cognitive perspectives.

Despite the growing body of empirical research on the impact of AI technology in the workplace, there is a lack of exploration of

Table 9 Comparison of the effects of AI technology application and employee responsibility.

	Production efficiency			Innovation performance	
	ELP	EOLS	EOP	PA	PE
	(1)	(2)	(3)	(4)	(5)
ER	0.004**	0.004**	0.005***	0.019**	0.001**
	[0.010]	[0.020]	[0.004]	[0.010]	[0.014]
AI	0.014**	0.009*	0.011**	−0.103	−0.002
	[0.016]	[0.075]	[0.043]	[0.255]	[0.750]
HHI	0.053	0.042	0.022	−1.275*	−0.122*
	[0.465]	[0.569]	[0.816]	[0.081]	[0.068]
SOE	0.002	0.017	−0.033	0.409**	0.065***
	[0.969]	[0.746]	[0.507]	[0.015]	[0.006]
Intercept	−0.923	−1.833*	0.426	4.541	0.245
	[0.189]	[0.052]	[0.309]	[0.282]	[0.375]
Control variables	Control	Control	Control	Control	Control
Industry	Control	Control	Control	Control	Control
Year	Control	Control	Control	Control	Control
R^2	0.4711	0.5629	0.3547	0.1884	0.2161
F	2347.962	2486.041	1897.127	75.916	15.467
N	12,936	12,936	13,300	13,549	2507

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

the relationship between AI and employee responsibility. Employees are a crucial stakeholder group for firms (Clarkson, 1995), and treating employees well and taking social responsibility can have positive effects on work attitudes, loyalty, job security, satisfaction, emotional attachment, and innovation participation, while reducing turnover intention (Gharleghi et al., 2018; Chun, 2009). However, this aspect has not been explored in recent empirical studies on the effects of AI technology in the workplace.

We found a negative relationship between the application of AI technology and employee responsibility. We think that there are mechanisms underlying the relationship between the application of AI technology and employee responsibility, such as changes in management objectives and the creation of new environmental structures that include supervision and incentives in multiple dimensions. We also found that supervision cost plays a partially mediating role in the relationship between the application of AI technology and employee responsibility. These findings help build a theoretical foundation and provide a new explanation for studies that have drawn more negative conclusions about the impact of AI technology in the workplace.

We have also further elucidated the contingent factors influencing the relationship between the application of AI technology and employee responsibility. Our findings reveal that the negative relationship between AI technology application and employee responsibility weakens with higher levels of product market competition and is more pronounced in government-controlled firms compared to privately controlled ones. The results suggest that firm's characteristics and operating environment play an important role in determining the extent to which they are affected by the application of AI technology. Previous studies have only hinted at, but never explicitly tested, the testable hypotheses we put forward.

We compared the effects of artificial intelligence technology and employee responsibility on a firm's production efficiency and innovation performance. Our findings indicate that both AI technology application and employee responsibility can enhance a firm's production efficiency, and employee responsibility also has a significant positive effect on innovation output and innovation efficiency. However, the application of AI technology does not have a significant impact on innovation output and innovation efficiency. The results suggest that in the era of artificial intelligence, the principle of "people-oriented" in human resource management and taking employee responsibilities still have a very important positive role.

Some previous theoretical studies have warned managers that relying on automated tools may lead to problems such as path dependence and lack of "human touch" between organizations and employees (Raisch and Krakowski, 2021). Managers need to look at the irreplaceable uniqueness of human intelligence and the threat of machine intelligence in human-machine cooperation system from a higher level, seeking the unity of contradictions (Lindebaum et al., 2020). This study tries to response to this and provide a better understanding of human and machine intelligence.

Our study has practical implications as well. With the extensive application of artificial intelligence technology in firms, management objectives, management ideas, and management methods have changed. In this process, firms may reduce the level of employee responsibility and break the relationship between firms and employees. For government supervision departments, on the one hand, relevant laws, policies, and supervision mechanisms should be improved as soon as possible to meet the development needs of human resource management in the era of artificial intelligence, urging firms to take employee responsibility, protect employees' legitimate rights and interests, and build healthy and harmonious labor relations. Artificial intelligence developers also need to pay attention to the various challenges brought about by the application of artificial intelligence in the workplace, consider the rights and interests of stakeholders affected by technology, and find various ways to eliminate, reduce, or "minimize" negative effects.

Firm managers need to realize that in the era of artificial intelligence, employee responsibility still has a very important positive role. They should treat the role of artificial intelligence technology dialectically and avoid relying too much on artificial intelligence technology while ignoring the uniqueness and subjectivity of human intelligence. Managers must also enhance their moral awareness, face up to the challenges brought by the application of artificial intelligence technology to the relationship between firms and employees, promote the better integration of employees and artificial intelligence, and realize the common development of technology, employees, and organizations.

It should be emphasized that although the research in this study finds that the application of AI technology is negatively related to a firm's employee responsibility, it cannot be said that the application of AI technology is a bad thing. AI technology has many advantages in improving efficiency and reducing costs. The key problem is how to make good use of these advantages and coordinate the relationship between AI and employees. In addition, due to the difficulty of data collection, this study only used the total word frequency of the keywords involving "artificial intelligence technology" in the annual reports of listed companies to measure the application degree of artificial intelligence technology in enterprises, without considering the heterogeneity of the starting time and application scope of artificial intelligence technology in each firm. Subsequent research can deeply analyze the effects of different types of AI technology applications and the effects of the length of application time on employee responsibility.

Data availability

Data on the company's AI technology applications, government ownership, sales, number of shares held by the largest and second-largest shareholders, TMT age, TMT gender, TMT tenure, TMT education, TMT occupational background, board size, number of independent directors, CEO and Chairman duality, company profit, executive shareholding, year of establishment, operating income, R&D expenditure, asset-liability ratio, and total assets can be obtained by accessing the China Stock Market & Accounting Research (http://www.gtarsc.com/). The employee responsibility index can be obtained from HeXun.com (www.hexun.com).

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Note

1 Data source: see https://www.theverge.com/2019/4/25/18516004/amazon-warehouse-fulfillment-centers-productivity-firing-terminations.

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JW, ZX, and RZ designed the research; JW and ZX performed the research; JW and RZ analyzed the data; JWa, ZX, and RZ wrote the first draft of the paper; JW and ZX provided useful edits, comments, and suggestions for this work. Zeyu Xing is both the first and sole corresponding author.

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The authors declare no competing interests.

Ethical approval
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This article does not contain any studies with human participants performed by any of the authors. All sources used in this study have been considered and cited.

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