参赛学生姓名： 沈陈菲、胡谷蓁溱、李怡辰

中学： 南京外国语学校

省份： 江苏省

国家/地区： 中国

指导老师姓名： 宋哲

指导老师单位： 南京大学商学院

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From Intelligence to Performance: How Artificial Intelligence Applications Improve Firms' Dual Performance

Chenfei Shen[1], Guzhenzhen Hu[1], Yichen Li[1], & Zhe Song[2]

1 Nanjing Foreign Language School, Nanjing, Jiangsu, China

2 School of Business, Nanjing University, Nanjing, Jiangsu, China

Abstract

Based on panel data of China's Shanghai and Shenzhen A-share listed firms from 2009 to 2023, this paper examines the impact of artificial intelligence (AI) applications on firms' financial performance and environmental performance from the perspective of resource dependence theory, focusing on the synergy between efficiency goals and sustainability goals. The results show that AI applications significantly enhance firms' dual performance, demonstrating their potential in improving both financial returns and environmental responsibility. Mechanism tests indicate that AI promotes performance improvement through three pathways: breaking innovation boundaries, enhancing firm reputation, and strengthening strategic cooperation. Further analysis shows that a higher proportion of highly educated human capital significantly strengthens the positive effects of AI on dual performance, while regional environmental regulation amplifies the role of AI in the environmental dimension. Additional analysis reveals clear firm heterogeneity: non-state-owned enterprises and high-tech enterprises benefit more; different types of AI technologies exert differentiated effects, with knowledge reasoning and representation technologies and computer vision showing stronger effects on financial performance, while differences in environmental performance are less pronounced; in heavily polluting industries, AI applications significantly improve firms' sustainability performance and promote green transformation. This study not only provides empirical evidence for understanding how AI applications support the realization of firms' dual goals, but also offers policy implications for firms and governments in designing strategies that integrate digitalization and green development.

Keywords: AI applications, financial performance, environmental performance, resource dependence

1. Introduction

With the continuous promotion of a series of policies, such as *Made in China 2025* (2015), *New Generation Artificial Intelligence Development Plan* (2017), *Intelligent Manufacturing Development Strategy* (2019), and *Guidelines on Deeply Implementing the "AI+" Initiative* (2025), the penetration of artificial intelligence (AI) into Chinese firms has accelerated. It has gradually become a key technology path for corporate transformation and upgrading. By 2024, the scale of China's AI industry had exceeded 700 billion RMB, maintaining an annual growth rate of over 20% for many years.

The unique value of AI lies in its ability to embed into financial management and decision-making processes to improve efficiency and profitability. At the same time, it can be applied to environmental governance and sustainable innovation to enhance green transformation and social responsibility. However, from the perspective of resource dependence theory, AI is essentially a resource-based tool. Its transformation into organizational capability depends on how firms obtain, allocate, and control external resources. In this process, efficiency goals and sustainability goals often coexist but also conflict. If firms overemphasize efficiency goals, AI may serve short-term financial returns first, while environmental performance is marginalized. Conversely, if firms overemphasize sustainability goals, AI may be allocated more to environmental responsibility and social effects, while financial returns may be delayed. Therefore, it is necessary to analyze the compatibility of dual goals in AI applications under the Chinese context.

Chinese firms generally face resource constraints when pursuing innovation and transformation (Gaddy et al., 2017). To balance efficiency and sustainability goals, firms need to rely on external stakeholders to obtain critical resources. As a core tool of digital transformation, AI is expected to help firms achieve dual goals by reallocating and concentrating resources. First, AI helps firms access external resources, such as data analysis and intelligent decision systems, which support both financial decisions and environmental governance. These resources allow firms to set more accurate financial goals and optimize their environmental responsibility. Second, AI is not only a tool for resource acquisition but also a means for efficient resource use. Through intelligent allocation and optimization, AI improves the efficiency of resource utilization, enabling firms to pursue short-term financial returns while reducing waste and improving environmental performance. Finally, AI is essentially a tool. Its effective use depends on a firm's own resource allocation and capability building. An effective AI application requires sufficient knowledge, technical skills, and human capital, combined with firm-specific needs and external conditions, to achieve coordination and win-win outcomes in financial and environmental goals. Thus, how firms allocate AI resources and ensure complementarity among different resources will directly affect their success in achieving dual performance goals.

As a core driver of strategic transformation, the value of AI lies not only in technological innovation but also in transforming from a "tool" into a "capability" through the identification, acquisition, and allocation of external resources. This enhances organizational adaptability and competitiveness. Existing studies mainly use dynamic capability theory to explain how digital elements become competitive advantages (Warner and Wäger, 2019; Fang and Liu, 2024), or use institutional theory and stakeholder perspectives to examine regulation and social expectations related to AI (Rana et al., 2024; Singh, 2024). However, most studies analyze only financial performance or environmental performance separately, and there is a lack of research on how AI achieves integration between the two. This gap makes it difficult to answer a key question: is an AI application a "double-edged sword," or can it truly help firms achieve win-win results in both financial and environmental dimensions?

This paper makes four contributions. First, it enriches the literature on the micro-level effects of digital technologies by providing firm-level evidence on AI applications. Second, it builds an integrated framework with financial–environmental dual performance as the target, placing efficiency and sustainability goals in the context of China's structural transformation, and revealing internal synergy mechanisms. Third, it extends research on the governance effects of AI by explaining its role from the perspective of resource acquisition, allocation, and utilization. Fourth, it analyzes how AI improves firms' dual performance through breaking innovation boundaries, enhancing firm reputation, and strengthening strategic cooperation, while examining the moderating roles of highly educated human capital and regional environmental regulation. These findings systematically reveal the mechanisms and contextual differences of AI applications in resource acquisition, allocation, and capability transformation, further enriching the explanatory power of resource dependence theory.

2. Literature Review and Theoretical Analysis

2.1 Literature Review

The first stream of literature related to this study focuses on the application effects of AI. On the financial side, AI has been shown to significantly improve efficiency and accuracy in automating financial processes (Davenport and Ronanki, 2018; Wamba et al., 2020), supporting intelligent decision-making (Chatterjee and Das, 2025; Verma et al., 2022), and enabling precise financial forecasting (Scholapurapu, 2025; Vancsura et al., 2025). However, the financial benefits are not universal, as some firms fail to see immediate improvement after adoption. Scholars have found that AI adoption often exhibits a "J-curve" effect, with short-term declines in productivity (Brynjolfsson et al., 2021; Marioni et al., 2024). Its value lies more in innovation and market expansion, while its effects on cost control and profit growth are limited (Babina et al., 2024; Zhang et al., 2023). Moreover, the financial impact of AI depends on the fit between firms and industries (Wamba, 2022; Abou-Foul et al., 2023), and it varies across supply chain and operational contexts (Wamba-Taguimdje et al., 2020; Cannas et al., 2024).

On the environmental side, AI has been widely applied to promote green production (Lin and Zhou, 2025; Zhou et al., 2024), strengthen carbon emission control (Priya et al., 2023; Ding et al., 2023), optimize green supply chain management (Benzidia et al., 2021; Yang et al., 2025), and improve environmental information disclosure quality (Zhao et al., 2025; Wu et al., 2025). However, similar to its financial effects, some firms use AI to expand non-clean production or obscure disclosure (Li et al., 2024; Khan et al., 2024; Ren et al., 2025), which undermines green transition and emission reduction goals. Overall, existing literature reveals tension between the potential value of AI applications and their practical constraints. This tension reflects a mismatch between resource acquisition and resource utilization in corporate governance. Whether AI can help firms mobilize and use resources to improve dual performance remains an open question.

Another stream of literature focuses on factors influencing firms' dual performance. Most studies consider financial performance or environmental performance separately, with few integrating them. Only a limited number of works examine how internal and external conditions affect dual performance differently. Xie et al. (2022) found that green process innovation improves both environmental performance and long-term financial outcomes. He et al. (2021) reported that eco-label certification enhances environmental performance but has limited effects on financial performance. Ali et al. (2021), using Malaysian industrial firm data, showed that effective integration of Industry 4.0 technologies and environmental assets can improve both environmental management and financial performance, thus achieving dual benefits.

These studies, however, do not fully capture the effects of AI applications in the Chinese context. To address this gap, this paper adopts the perspective of Resource Dependence Theory (RDT), viewing AI not as a simple adoption of technology but as a mechanism for reconfiguring firms' dependence relationships and power structures with key resources. The introduction of AI reshapes firms' exchange and control relationships with multiple actors. The strength, concentration, and substitutability of these dependencies, as well as the associated bargaining power and governance arrangements, determine whether AI can be effectively transformed into organizational capabilities serving both financial and environmental goals. In the Chinese context, AI supply is developing rapidly with platform-based concentration, and regional differences exist in data governance. Firms need not only to "acquire" key resources but also to complete a secondary process of "allocation–integration–governance" internally. That is, they must ensure sustainable access to data and computing power, allocate them to processes that both reduce costs and enhance compliance, and transform temporary capabilities into stable organizational ones through cross-functional incentives and disclosure. Therefore, there is an urgent need to develop an analytical framework based on resource dependence structures and internal orchestration mechanisms to reveal the role of AI in financial and environmental dual performance.

2.2 Theoretical Hypotheses

2.2.1 AI Applications and Firms' Dual Performance

The fundamental attribute of AI lies in its resource nature. It not only provides firms with channels to access external key resources but also strengthens the efficiency of resource utilization through technological capabilities and plays a role in resource allocation and reallocation within governance structures. This implies that adopting AI does not inherently guarantee better performance. Instead, firms must apply it in the complex processes of resource acquisition, allocation, and control to ensure that it truly serves organizational goals. Thus, the role of AI can be understood as a process in which firms restructure external relations and internal capabilities within the framework of resource dependence. Its effects on financial and environmental performance reflect the interaction and balance between efficiency logic and sustainability logic.

For efficiency goals, AI improves financial performance in three main ways. First, it enhances the automation of financial processes, achieving cost savings and efficiency improvements, such as identifying key errors and seeking optimal solutions (Rabbani et al., 2023; Elias et al., 2024; Shirzad and Rahmani, 2024; Davenport and Ronanki, 2018). Second, AI, through intelligent analysis and predictive models, helps firms identify market trends, competitive patterns, and investment opportunities more efficiently, thereby optimizing resource allocation in capital budgeting and strategic decision-making, improving capital use efficiency, and enhancing profitability (Chatterjee et al., 2021; Montanaro et al., 2024; Jain and Kulkarni, 2023). Finally, AI provides forward-looking support in risk management. Using predictive analysis to anticipate cash flows and market fluctuations helps firms identify potential crises early and adjust resources accordingly, thus improving overall financial stability (Lee, 2020; Fritz-Morgenthal et al., 2022; Mushtaq et al., 2022; Milana and Ashta, 2021). Through these dual mechanisms of resource acquisition and utilization, AI makes financial management more flexible, transparent, and efficient, thereby significantly improving firms' financial performance.

For sustainability goals, AI influences environmental performance in three ways. First, it reduces resource waste and energy consumption through real-time monitoring and dynamic optimization, thereby increasing the utilization rate of raw materials and reducing waste emissions (Mhlanga, 2023; Fu et al., 2024; Liu et al., 2025). Second, by relying on IoT and big data analysis, AI integrates multi-source environmental data, helping firms more accurately identify pollution risks and make scientific environmental management decisions (Guo et al., 2019; Himeur et al., 2022; Chang et al., 2023). Finally, the adoption of AI promotes green collaboration and compliance within supply chains. Its ability to optimize logistics and supplier management not only reduces the overall carbon footprint but also lowers environmental compliance risks through automated regulation analysis (Zamani et al., 2023; Condé and Münch, 2025; Dauvergne, 2022; Thimm, 2023). Together, these mechanisms make AI an important tool for improving environmental performance and fulfilling social responsibility.

In sum, AI shows potential in promoting both financial and environmental performance, but its effects are not automatic. They are shaped by channels of resource acquisition, internal capability structures, and external institutional environments. Whether firms can achieve a dynamic balance between efficiency and sustainability goals determines the ultimate effectiveness of AI applications. In summary, this paper proposes the following hypotheses:

H1a: AI applications have a positive effect on firms' financial performance.

H1b: AI applications have a positive effect on firms' environmental performance.

2.2.2 The Mediating Role of Innovation Boundaries

The improvement of firms' financial performance and environmental performance fundamentally depends on the acquisition and utilization of key resources. Whether for market expansion, technology development, or compliance response, firms need to access or integrate external knowledge, technologies, and capital. However, these key resources are often controlled by external actors. With limited internal resources, firms must break internal boundaries to extend and transform resources. The rise of AI provides new opportunities. AI allows firms to identify and use external resources at lower information costs and with higher efficiency, laying a foundation for achieving both financial and environmental goals.

However, acquiring key resources is usually accompanied by uncertainty, constraints, and high costs. Their utilization efficiency is also limited by path dependence and knowledge barriers, which restrict improvements in financial performance. AI, with its strong data processing, pattern recognition, and knowledge management capabilities, can ease these constraints (Haenlein et al., 2019; Oppioli et al., 2023; Eshraghi and Smith, 2023). On the one hand, AI applications scan and analyze massive external data efficiently, quickly identifying cross-domain technology opportunities and market trends, thus reducing information asymmetry and uncertainty in innovation search (Celik, 2023). On the other hand, AI promotes the absorption, connection, and recombination of heterogeneous knowledge, helping firms overcome traditional innovation path dependence and enabling resource reconfiguration across multiple fields (Kaplan and Haenlein, 2020; Grashof and Kopka, 2023). These capabilities create conditions for breaking innovation boundaries, making firms more proactive in exploring and integrating new knowledge and resources, thereby opening new possibilities for financial growth.

Breaking innovation boundaries expands knowledge breadth and provides new support for stable financial performance. By broadening innovation scope, firms can identify and develop more diverse products, services, and market opportunities, reducing dependence on single businesses and improving profit stability. Cross-domain knowledge sharing and resource integration also enhance the efficiency of R&D infrastructure and complementary assets, lowering unit innovation costs. More importantly, mastering a wider portfolio of frontier technologies allows firms to build stronger intellectual property barriers and competitive advantages, increasing profit margins and enabling continuous improvement of financial performance in complex market environments.

For environmental performance, breaking innovation boundaries is equally important. Firms' green transformation and compliant production often rely on specific key technologies, and dependence on a single path may limit further improvement in environmental outcomes. AI introduces new possibilities: on the one hand, it integrates environmental knowledge into existing technical systems, promoting deep integration of green concepts with core businesses, and forming “green + core business” innovation models that improve energy efficiency and pollution control at the source (Ozturk and Ullah, 2022). On the other hand, AI’s human–machine interaction capabilities help firms better identify and understand complex environmental regulations and diverse stakeholder demands. Through generative analysis and solution recommendations, AI provides knowledge and innovative approaches, thus improving compliance efficiency and environmental responsiveness (Kaushik and Walsh, 2019). In this way, AI applications in environmental innovation not only expand green development paths but also provide strong support for the continuous improvement of environmental performance.

In summary, this paper proposes the following hypotheses:

H2a: AI applications are positively related to firms’ innovation breadth. Breaking innovation boundaries mediates the effect of AI applications on firms’ financial performance.

H2b: AI applications are positively related to firms’ innovation breadth. Breaking innovation boundaries mediates the effect of AI applications on firms’ environmental performance.

2.2.3 The Mediating Role of Firm Reputation

The improvement of financial performance largely depends on the inflow of external key resources. However, such resources are often controlled by external stakeholders, including capital markets, financial institutions, and customers. Firms themselves often face resource constraints. Therefore, reputation serves as a critical bridge in this process, enabling firms to win external trust by building and maintaining a positive image. This trust encourages external actors to allocate more resources, which in turn supports improvements in both financial and environmental performance.

AI applications are an important factor influencing reputation. On the one hand, the introduction of AI technologies easily attracts media coverage and public attention, giving firms greater visibility and positive evaluations. On the other hand, rating agencies increasingly regard AI adoption as an indicator of strategic foresight and technological capability, which may lead to higher ratings. At the same time, AI enables firms to better understand consumer needs, optimize business processes, and improve service experience, helping them accumulate positive word of mouth and market trust (Le, 2023; Arduini et al., 2024; von Berlepsch et al., 2024). These factors jointly contribute to sustained reputation improvement.

Moreover, an enhanced reputation provides a mediating channel through which AI affects financial and environmental performance. For financial performance, reputable firms are more likely to gain bank credit and attract potential investors, which lowers financing costs and enhances profitability and stability (Weigelt and Camerer, 1988; Brammer and Pavelin, 2006; Odriozola and Baraibar-Diez, 2017). For environmental performance, firms with strong reputations often face greater external scrutiny and stakeholder expectations. This compels them to reinforce sustainability goals, adopt stricter environmental standards, and increase green investments to consolidate their responsible public image. Thus, reputation is not only an additional effect of AI applications but also a key bridge in the pathway through which financial and environmental performance improve.

In summary, this paper proposes the following hypotheses:

H3a: AI applications are positively associated with reputation, and higher reputation mediates the impact of AI on financial performance.

H3b: AI applications are positively associated with reputation, and higher reputation mediates the impact of AI on environmental performance.

2.2.4 The Mediating Role of Strategic Cooperation

The effective application of AI technologies relies not only on firms' internal technological reserves but also on data, algorithms, computing power, and supporting infrastructure from external partners. A single firm often cannot fully control these key elements, and must build connections with external actors to achieve deep AI applications (Hillman et al., 2009; Drees and Heugens, 2013). At the same time, strategic cooperation provides an important channel for overcoming resource bottlenecks. By introducing and sharing external resources, it helps firms alleviate resource dependence when pursuing both financial and environmental performance. The complexity and cross-domain nature of AI further intensify firms' need for external cooperation and highlight the critical role of strategic cooperation in enhancing dual performance.

Strategic cooperation plays a significant role in improving financial performance. On the one hand, alliances open new market channels and growth opportunities, while synergies reduce operating costs and increase efficiency, thereby strengthening profitability (Stuart, 2000; Van Beers and Zand, 2014). On the other hand, cooperation helps firms access advanced technologies and innovation resources more quickly, shorten R&D cycles, and enhance product competitiveness and market share. In addition, long-term stable partnerships strengthen brand reputation and market trust, attracting more investment and financing, lowering capital costs, and enhancing financial stability. Through these mechanisms, strategic cooperation serves as a key bridge linking AI applications to financial performance.

In terms of environmental performance, strategic cooperation also plays a positive role. By sharing resources and exchanging information with partners, firms can carry out joint innovation in green technology R&D, green supply chain optimization, and sustainable management, thereby reducing energy consumption and pollution (Sardana et al., 2020). More importantly, the involvement of diverse stakeholders in cooperation encourages firms to place greater emphasis on environmental responsibility when formulating strategies, helping balance efficiency and sustainability goals. Cooperation also creates conditions for firms to enter green markets, enabling them to cope with increasingly strict environmental regulations and consumer demand for green products. At the same time, partners' experience sharing and technical support accelerate the application and diffusion of green technologies, enhancing efficiency and capacity in environmental governance, and ultimately improving environmental performance (Horbach et al., 2012).

In summary, this paper proposes the following hypotheses:

H4a: AI applications are positively associated with strategic cooperation, and alliances mediate the impact of AI on financial performance.

H4b: AI applications are positively associated with strategic cooperation, and alliances mediate the impact of AI on environmental performance.

2.2.5 The Moderating Role of Human Capital Structure

AI as a resource-based tool depends not only on the advancement of the technology itself but also on whether firms have the ability to absorb, understand, and apply it. In this process, human capital structure reflects a firm's capacity to use AI. Employees with higher education, with richer knowledge reserves and stronger learning ability, can improve firms' understanding and use of AI. This strengthens the value of AI in achieving both financial and environmental goals.

For financial performance, highly educated employees have solid professional knowledge and strong technical skills. They can master the logic of AI more quickly and promote its integration with financial management in practice. This human capital advantage helps firms maximize the efficiency of AI in acquiring, using, and allocating resources, thereby optimizing operations, improving productivity, and reducing costs (Brynjolfsson and McAfee, 2014; Bessen, 2019; Huang and Ding, 2020). At the same time, these employees have a stronger strategic vision and market insight. They can identify technology trends and market opportunities, and push the application of AI in new product development and business model innovation, expanding profit opportunities (Zhou and Lee, 2021). Thus, the presence of highly educated employees reinforces the effect of AI on efficiency goals, making its impact on financial performance more significant.

For environmental performance, highly educated employees often have systematic thinking and long-term vision. They can provide reasonable suggestions during the application of AI, helping firms balance efficiency and sustainability goals and allocate resources toward sustainability. Specifically, these employees can better understand environmental regulation and green market demand, and combine AI with green production and energy-saving solutions. This promotes the application of AI in circular production, energy management, and other environmental practices (Wu and Zhang, 2020). In this way, highly educated employees help firms balance efficiency logic and sustainability logic, maximize the environmental benefits of AI, and effectively improve environmental performance.

In summary, this paper proposes the following hypotheses:

H5a: The proportion of highly educated employees positively moderates the relationship between AI applications and firms' financial performance.

H5b: The proportion of highly educated employees positively moderates the relationship between AI applications and firms' environmental performance.

2.2.6 The Moderating Role of Regional Environmental Regulation

The effect of AI applications depends not only on the advancement of the technology but also on whether firms can allocate and use resources effectively under specific institutional conditions. In this process, regional environmental regulation plays a key role. Strict environmental regulation not only increases external pressure on firms but also forces them to re-balance efficiency and sustainability goals under limited resources. As an external constraint, regulation directly affects how firms allocate AI resources to financial and environmental goals.

Regional environmental regulation can, to some extent, change firms' investment in environment-oriented resources, but its effect on financial performance is limited. In detail, the regulation mainly pushes firms to increase compliance costs and environmental spending. These affect the redistribution of resources toward environmental and sustainability areas rather than directly improving efficiency in financial logic. Moreover, AI in financial management, production optimization, and cost control mainly relies on firms' internal absorption and application abilities and is not strongly influenced by regulation. In addition, regulation aims to restrict environmental behavior (Wu et al., 2020), which is different from the profit-seeking aim of firms. Therefore, the strength of regulation does not significantly change the core value of AI in efficiency improvement and cost reduction.

However, for environmental performance, stronger regulation provides clear incentives and constraints (such as pollution fees and environmental subsidies) and higher compliance requirements. These push firms to allocate more resources to green production and energy-saving practices (Wang and Shen, 2016). In this process, firms not only face compliance pressure but also seek new technological paths to reduce environmental costs and achieve sustainability goals. AI provides strong support for such reallocation by improving efficiency in energy scheduling, pollution control, and green process innovation. Through real-time monitoring, dynamic optimization, and process improvement, AI helps firms reduce emissions and negative externalities, thus improving environmental performance more significantly.

In summary, this paper proposes the following hypotheses:

H6a: Regional environmental regulation does not significantly affect the relationship between AI applications and firms' financial performance.

H6b: Regional environmental regulation positively moderates the relationship between AI applications and firms' environmental performance.

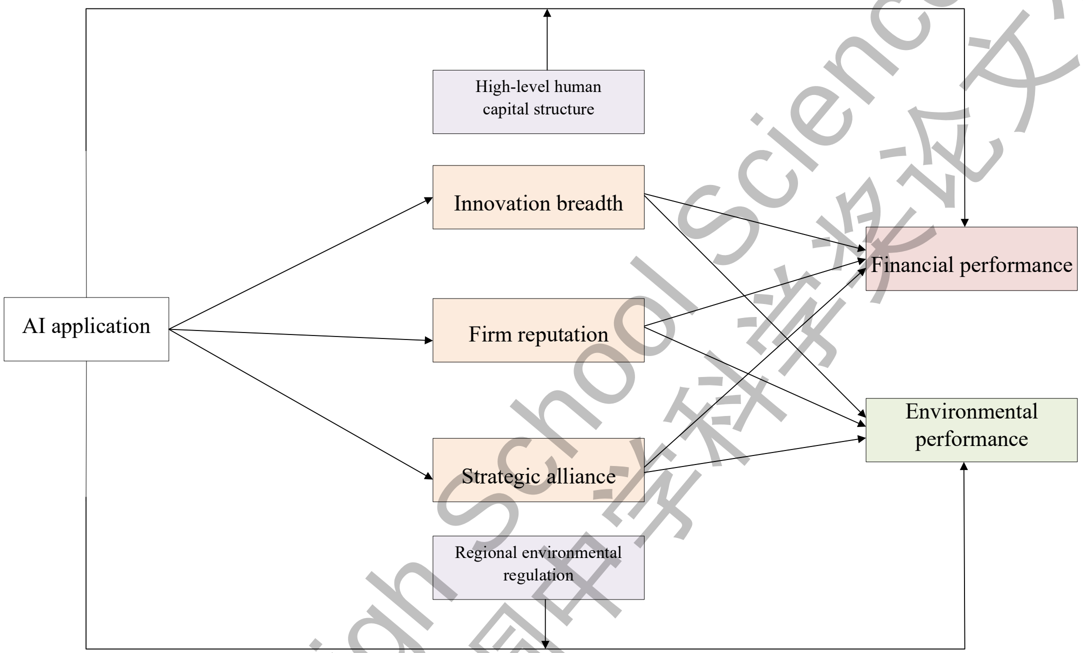


Figure 1. Theoretical analysis framework diagram

3. Research Design

3.1 Sample Data

This study uses listed firms on China's Shanghai and Shenzhen A-share markets as the research sample. The sample period is from 2009 to 2023. The year 2009 is chosen as the starting point for two reasons. First, since 2009, the application of AI-related technologies in Chinese firms has grown rapidly, and related disclosure information has become more abundant, ensuring the feasibility and continuity of the study. Second, after 2009, disclosure of AI and related fields in annual reports of listed firms became more standardized, and data quality improved. The year 2023 is the latest year with available data.

Data for this study are sourced from the following: annual reports of publicly listed companies are retrieved from CNINFO (http://www.cninfo.com.cn), while financial and environmental performance data are obtained from the CSMAR and Wind databases, respectively.

To ensure the reliability and validity of the data, we apply the following procedures:

(1) exclude firms in the financial industry;

(2) exclude samples with incomplete disclosure or missing key variables;

(3) exclude firms under ST or *ST status in that year;

(4) winsorize continuous variables at the 1% and 99% levels to reduce the influence of extreme values.

After these procedures, the final sample includes 4,842 firms, resulting in 34,271 firm-year observations of an unbalanced panel dataset.

3.2 Variable Definitions

1. Explanatory Variable

AI_utilize. Following Mishra et al. (2022), this study uses a machine learning method to construct a dictionary of AI-related terms to measure the level of AI application by firms. The construction steps are as follows:

(1) Annual reports of listed firms are obtained from CNINFO. Texts are formatted into txt files and segmented using the Jieba Chinese word segmentation library. To avoid splitting core AI terms, manually selected AI-related words are added to the Jieba user-defined dictionary.

(2) Based on industry research reports and AI term lists published by international organizations (e.g., IMF), seed words are set as "machine learning," "natural language processing," "computer vision," and "knowledge representation."

(3) The Skip-gram model in Word2vec is applied. Using 20% of the listed firm data randomly sampled from the corpus, the cosine similarity between seed words and other words is calculated. For each seed word, the 10 most semantically similar words are selected, and irrelevant or low-frequency words are removed to form an extended dictionary.

(4) Annual report texts are matched with the AI dictionary. The number of AI-related keywords in each annual report is counted, then plus one, and logged. This generates the indicator of firms' AI application, *AI_utilize*.

2. Explained Variables

Financial performance: Common indicators include market-based indicators (e.g., Tobin's Q) and accounting-based indicators (e.g., return on assets, return on equity). As this study focuses on listed firms, and return on assets (*ROA*) reflects a firm's ability to generate net income with total assets, *ROA* is chosen as the measure of financial performance. *ROA* is calculated as:

ROA = Net profit / Total assets × 100%.

A higher ROA indicates higher efficiency in using assets to create income and better financial performance.

Environmental performance: Environmental performance is assessed based on 25 indicators across five areas: environmental information carriers, management practices, liabilities, regulatory compliance and certifications, and overall governance. Each indicator is assigned a score between 0 and 2, based on the quality of the information disclosed. The cumulative score reflects the firm's environmental performance.

3. Mediating Variables

Innovation breadth: This is calculated using the International Patent Classification (IPC) codes of firms' patents. The IPC format for Chinese patents is "Section–Class–Subclass–Main group–Subgroup." For example, "A01B01/00," where the first letter indicates one of the eight sections (A: human necessities; B: operations and transport; C: chemistry and metallurgy; D: textiles and paper; E: fixed constructions; F: mechanical engineering, lighting, heating, weapons, blasting; G: physics;

H: electricity).

To capture innovation breadth more accurately, this study introduces the concept of knowledge breadth and uses the Herfindahl-Hirschman Index (HHI) at the main group level. The formula is:

$$Innov_{hhi} = 1 - \sum(\frac{Z_{imt}}{Z_{it}})^2 \qquad (1)$$

where Zimt is the number of patents granted to firm *i* in year *t* under main group *m*, and Zit is the total number of patents of firm *i* in year *t* across all main groups. A larger value of Innov_hhi indicates broader innovation across more technical fields.

In the calculation, two treatments are applied: (1) only invention patents and utility model patents are included, while design patents are excluded to avoid underestimating knowledge expansion; (2) withdrawn or abandoned and invalid patent applications are excluded.

Firm reputation: Following Meijer and Kleinnijenhuis (2006), firm reputation is measured as the natural logarithm of one plus the sum of positive reports in online and print media each year.

Strategic alliance: Based on announcements disclosed by listed firms, this study identifies whether a firm participates in a strategic alliance in a given year. For alliances with a disclosed cooperation period, if the period is five years, the alliance is regarded as effective from year *t* to *t+5*. For alliances without disclosed periods, following Chen et al. (2015), the effective period is set as three years. A dummy variable **Alliance** is constructed: if a firm forms or remains in an effective alliance in year *t*, the value is 1; otherwise, the value is 0.

4. Moderating Variables

Highly educated human capital structure: This is measured as the proportion of employees with doctoral degrees. This reflects the concentration of human capital in terms of education level and represents talent reserves for knowledge-intensive activities. Following Park and Shaw (2013), the share of highly educated employees is regarded as an important indicator of firms' knowledge resources and innovation capability, directly influencing strategy execution and technological innovation. Thus, the proportion of doctoral employees effectively captures highly educated human capital.

Regional environmental regulation: This is measured by the frequency of the term "environmental protection" in provincial government work reports each year. The ratio of this frequency to the total word count of the report indicates the level of environmental regulation. A higher value suggests stronger regional environmental regulation.

5. Control Variables

Control variables include firm size (*Size*), cash flow (*Cashflow*), inventory ratio (*INV*), revenue growth (*Growth*), CEO duality (*Dual*), ownership of top 10 shareholders (*Top10*), ownership balance (*Balance*), firm age (*Firmage*), and number of employees (*Employ*). Year, industry, and province fixed effects are also controlled.

Table 1. Variable Definitions and Descriptions

Variable Type	Variable Name	Symbol	Definition
Explanatory	AI application	*AI_utilize*	Number of AI-related words in annual report / total words in annual report
	Financial performance	*ROA*	(Net profit / Total assets) * 100%
Dependent	Environmental performance	*EP*	Sum of 25 evaluation indicators of environmental performance (0, 1, 2)
Mediating	Innovation breadth	*Innov_hhi*	Calculated at patent group level based on

			Herfindahl index
	Firm reputation	*Reputation*	Ln (number of positive online and newspaper reports each year + 1)
	Strategic alliance	*Alliance*	Obtained from strategic alliance announcements
Moderating	High-level human capital structure	*High_edu*	Proportion of employees with doctoral degrees
	Regional environmental regulation	*Regulation*	Share of environmental regulation terms in provincial government reports
	Firm size	*Size*	Ln (total assets at year-end)
	Cash flow	*Cashflow*	Net operating cash flow / total assets
	Inventory ratio	*INV*	(Inventory / Total assets) * 100%
	Revenue growth rate	*Growth*	(Current year revenue / Previous year revenue) - 1
	CEO duality	*Dual*	=1 if chairman and CEO are the same person, otherwise =0
Control	Top 10 shareholders' shareholding	*Top10*	Shares held by top 10 shareholders / total shares
	Ownership balance	*Balance*	Shareholding of 2nd – 5th largest shareholders / shareholding of largest
	Firm age	*Firmage*	Ln (current year – year of establishment + 1)
	Number of employees	*Employ*	Total number of employees
	Year	Year	Year fixed effect
	Industry	Industry	Industry fixed effect
	Province	Province	Province fixed effect

3.3 Model Specification

To test Hypothesis 1 on the effect of AI applications on firms' dual performance, the following model is constructed. Here, *i* denotes firm, *t* denotes year, *Controls* are the control variables defined earlier, ε is the random error term, *Year* denotes year fixed effects, *Industry* denotes industry fixed effects, and *Province* denotes province fixed effects. If Hypothesis 1 holds, the coefficient α_0 is expected to be significantly positive.

$$ROA_{i,t}/EP_{i,t} = \alpha_0 AI\_utilize_{i,t} + \Sigma Controls_{i,t} + \Sigma Year + \Sigma Industry + \Sigma Province + \varepsilon_{i,t} \quad (2)$$

To test Hypothesis 2 on the mediating role of innovation breadth, the following mediation models are constructed. If β_0 in Equation (4) is significant, mediation exists. If γ_0 in Equation (5) is not significant while γ_1 is significant, full mediation exists. If both γ_0 and γ_1 are significant, partial mediation exists.

$$ROA_{i,t}/EP_{i,t} = \alpha_0 AI\_utilize_{i,t} + \Sigma Controls_{i,t} + \Sigma Year + \Sigma Industry + \Sigma Province + \varepsilon_{i,t} \quad (3)$$

$$Innov\_hhi_{i,t} = \beta_0 AI\_utilize_{i,t} + \Sigma Controls_{i,t} + \Sigma Year + \Sigma Industry + \Sigma Province + \varepsilon_{i,t} \quad (4)$$

$$ROA_{i,t}/EP_{i,t} = \gamma_0 AI\_utilize_{i,t} + \gamma_1 Innov\_hhi_{i,t} + \Sigma Controls_{i,t} + \Sigma Year + \Sigma Industry + \Sigma Province + \varepsilon_{i,t} \quad (5)$$

To test Hypothesis 3 on the mediating role of firm reputation, the following models are constructed. If μ_0 in Equation (7) is significant, mediation exists. If θ_0 in Equation (8) is not significant while θ_1 is significant, full mediation exists. If both θ_0 and θ_1 are significant, partial mediation exists.

$$ROA_{i,t}/EP_{i,t} = \alpha_0 AI\_utilize_{i,t} + \Sigma Controls_{i,t} + \Sigma Year + \Sigma Industry + \Sigma Province + \varepsilon_{i,t} \tag{6}$$

$$Reputation_{i,t} = \mu_0 AI\_utilize_{i,t} + \Sigma Controls_{i,t} + \Sigma Year + \Sigma Industry + \Sigma Province + \varepsilon_{i,t} \tag{7}$$

$$ROA_{i,t}/\mathrm{EP}_{i,t} = \theta_0 AI\_utilize_{i,t} + \theta_1 Reputation_{i,t} + \Sigma Controls_{i,t} + \Sigma Year + \Sigma Industry + \Sigma Province + \varepsilon_{i,t} \tag{8}$$

To test Hypothesis 4 on the mediating role of strategic alliance, the following models are constructed. If λ_0 in Equation (10) is significant, mediation exists. If φ_0 in Equation (11) is not significant while φ_1 is significant, full mediation exists. If both φ_0 and φ_1 are significant, partial mediation exists.

$$ROA_{i,t}/EP_{i,t} = \alpha_0 AI\_utilize_{i,t} + \Sigma Controls_{i,t} + \Sigma Year + \Sigma Industry + \Sigma Province + \varepsilon_{i,t} \tag{9}$$

$$Alliance_{i,t} = \lambda_0 AI\_utilize_{i,t} + \Sigma Controls_{i,t} + \Sigma Year + \Sigma Industry + \Sigma Province + \varepsilon_{i,t} \tag{10}$$

$$ROA_{i,t}/\mathrm{EP}_{i,t} = \varphi_0 AI\_utilize_{i,t} + \varphi_1 Alliance_{i,t} + \Sigma Controls_{i,t} + \Sigma Year + \Sigma Industry + \Sigma Province + \varepsilon_{i,t} \tag{11}$$

To test the moderating role of human capital structure with high educational background, the following moderation model is constructed. Here, $High\_edu_{i,t}$ represents the proportion of highly educated employees in firm *i* at year *t*, and the interaction term $High\_edu_{i,t} \times AI\_utilize_{i,t}$ captures the moderating effect. If ω_1 in Equation (12) is significantly positive, Hypothesis H5 is supported.

$$ROA_{i,t}/EP_{i,t} = \omega_0 AI\_utilize_{i,t} + \omega_1 High\_edu_{i,t} \times AI\_utilize_{i,t} + \omega_2 High\_edu_{i,t} + \Sigma Controls_{i,t} + \Sigma Year + \Sigma Industry + \Sigma Province + \varepsilon_{i,t} \tag{12}$$

To test the moderating role of regional environmental regulation, the following moderation models are constructed. Here, $Regulation_{i,t}$ represents the level of regional environmental regulation faced by firm *i* in year *t*, and the interaction term $Regulation_{i,t} \times AI\_utilize_{i,t}$ captures the moderating effect. If σ_1 in Equation (13) is not significant while π_1 in Equation (14) is significantly positive, Hypothesis H6 is supported.

$$ROA_{i,t} = \sigma_0 AI\_utilize_{i,t} + \sigma_1 Regulation_{i,t} \times AI\_utilize_{i,t} + \sigma_2 Regulation_{i,t} + \Sigma Controls_{i,t} + \Sigma Year + \Sigma Industry + \Sigma Province + \varepsilon_{i,t} \tag{13}$$

$$EP_{i,t} = \pi_0 AI\_utilize_{i,t} + \pi_1 Regulation_{i,t} \times AI\_utilize_{i,t} + \pi_2 Regulation_{i,t} + \Sigma Controls_{i,t} + \Sigma Year + \Sigma Industry + \Sigma Province + \varepsilon_{i,t} \tag{14}$$

In addition, to address potential heteroskedasticity across industries, the standard errors of regression coefficients in all models are clustered at the industry level.

4. Empirical Analysis

4.1 Descriptive Statistics

Table 2 provides the descriptive statistics for the key variables. The average *ROA* is 0.0403, with a median of 0.0411 and a standard deviation of 0.0777, suggesting relatively stable profitability across firms, though there are notable variations. The average *EP* stands at 1.743, with a median of 1, a standard deviation of 2.003, and a maximum value of 9. This shows that most firms perform modestly in environmental management and disclosure, while only a few firms reach a high level. The core explanatory variable *AI_utilize* has a mean of 0.0866, a median of 0, and a standard deviation of 0.344. This suggests that most firms disclose little about AI, while only a small number of firms show a high level of application, with the distribution being right-skewed.

Regarding control variables, *Size* has a mean of 22.16, indicating a reasonable distribution of asset scale. The mean value of *Cashflow* is 0.0488, within a normal range. The mean of *INV* is 0.141, with a median of 0.111, suggesting some differences in asset structure across firms. The mean of

Growth is 4.285, but with a large standard deviation and some extreme values, showing significant variation in growth rates.

For corporate governance and basic characteristics, the mean proportion of *Indep* is 37.54%, meeting regulatory requirements. The mean value of *Dual* is 0.288, meaning that about 30% of firms have the same person serving as both chairman and general manager. The mean shareholding ratio of *Top10* is 0.595, indicating high ownership concentration. The mean of *Balance* is 0.364, showing some degree of internal power balance. *FirmAge* corresponds to about 17 years on average. The mean number of employees is 5,951, but with large variation. Overall, the descriptive features of the variables align well with theoretical predictions, offering a reliable foundation for the following empirical investigation.

Table 2. Descriptive Statistics Results

Variable	N	mean	sd	p50	min	max
ROA	34271	0.0403	0.0777	0.0411	-2.834	0.786
EP	34271	1.743	2.003	1	0	9
AI_utilize	34271	0.0866	0.344	0	0	4.127
Size	34271	22.16	1.342	21.95	15.58	28.64
Cashflow	34271	0.0488	0.0751	0.0482	-0.744	0.876
INV	34271	0.141	0.131	0.111	0	0.943
Growth	34271	4.285	727.2	0.110	-1.309	134607
Board	34271	2.125	0.200	2.197	1.099	2.890
Indep	34271	37.54	5.561	36.36	14.29	80
Dual	34271	0.288	0.453	0	0	1
Top10	34271	0.595	0.155	0.608	0.0359	1.012
Balance	34271	0.364	0.287	0.286	0.00130	1
FirmAge	34271	2.880	0.367	2.944	0	4.174
Employ	34271	5951	20867	1886	1	570060

4.2 Baseline Regression Tests

Table 3 summarizes the baseline regression outcomes regarding the impact of *AI_utilize* on firms' dual performance. In Column (1), when only year, industry, and province fixed effects are considered, the coefficient of *AI_utilize* on *ROA* is estimated at 0.003 and shows significance at the 1% level. Column (2) indicates that, after incorporating additional control variables, the coefficient remains significantly positive at the 1% level, thereby confirming Hypothesis H1a. Column (3) reports the association between *AI_utilize* and *EP*. Under the setting with only year, industry, and province effects, the coefficient is 0.209 and is significant at the 10% level. Column (4) further shows that after accounting for control variables, the coefficient rises to 0.276 and achieves 1% significance, lending support to Hypothesis H1b.

Table 3. Baseline Regression Analysis

	(1)	(2)	(3)	(4)
	ROA	*ROA*	*EP*	*EP*
AI_utilize	0.003***	0.005***	0.209*	0.276***
	(4.901)	(6.418)	(1.817)	(3.271)

Size		0.001		0.589***
		(1.692)		(14.083)
Cashflow		0.357***		1.062***
		(7.010)		(3.279)
INV		0.015		0.095
		(1.538)		(0.376)
Growth		-0.000		-0.000***
		(-0.078)		(-7.469)
Board		-0.000		0.539***
		(-0.156)		(4.500)
Indep		-0.000		0.004
		(-1.522)		(0.780)
Dual		0.004***		-0.177***
		(2.946)		(-4.691)
Top10		0.089***		0.308**
		(13.747)		(2.710)
Balance		-0.005		-0.058
		(-1.553)		(-0.973)
FirmAge		-0.006***		0.109
		(-3.678)		(1.466)
Employ		-0.000***		0.000
		(-4.279)		(0.910)
Industry	*Yes*	*Yes*	*Yes*	*Yes*
Year	*Yes*	*Yes*	*Yes*	*Yes*
Province	*Yes*	*Yes*	*Yes*	*Yes*
_cons	0.040***	-0.034	1.725***	-13.114***
	(703.412)	(-1.152)	(173.513)	(-13.876)
N	34271	34271	34271	34271
R2_a	0.031	0.183	0.152	0.310

4.3 Mediation Effect Tests

(1) Breaking Innovation Boundaries

To examine the mediating effect of innovation breadth, a three-step regression procedure is first employed, followed by the Sobel test for robustness verification. The findings are summarized in Table 4. Column (1) indicates that the coefficient of *AI_utilize* is significantly positive at the 1% level, suggesting that AI adoption substantially expands firms' innovation breadth. When innovation breadth is incorporated into the regression model, Columns (2) and (3) reveal that the coefficients of *Innov_hhi* are both significantly positive, implying that broader innovation scope enhances financial as well as environmental performance. At the same time, the coefficients of *AI_utilize* remain significant but decrease relative to the baseline, showing that innovation breadth serves as a partial channel through which AI promotes performance. The Sobel Z statistics are 5.957 and 9.752, both significant at the 1% threshold. Overall, AI applications enable firms to integrate diverse knowledge, overcome innovation barriers, and generate new development opportunities, thereby supporting the realization of dual objectives in profitability and sustainability. Hence, Hypothesis 2 is confirmed.

Table 4. Regression Results-Mediating Effect of Innovation Breadth

	(1)	(2)	(3)
	Innov_hhi	*ROA*	*EP*
Innov_hhi		0.007**	0.149*
		(2.720)	(1.895)
AI_utilize	0.037***	0.004***	0.271***
	(3.600)	(6.665)	(3.324)
Size	0.045***	0.001	0.582***
	(6.904)	(1.350)	(13.467)
Cashflow	0.086**	0.357***	1.049***
	(2.156)	(7.032)	(3.156)
INV	0.011	0.015	0.094
	(0.231)	(1.538)	(0.375)
Growth	0.000***	-0.000	-0.000***
	(8.927)	(-0.360)	(-8.347)
Board	0.035**	-0.001	0.534***
	(2.844)	(-0.230)	(4.463)
Indep	-0.001	-0.000	0.004
	(-1.161)	(-1.506)	(0.796)
Dual	0.004	0.004***	-0.178***
	(1.280)	(2.923)	(-4.760)
Top10	-0.035	0.089***	0.313**
	(-1.104)	(13.853)	(2.773)
Balance	-0.000	-0.005	-0.058
	(-0.034)	(-1.552)	(-0.977)
FirmAge	-0.027**	-0.006***	0.113
	(-2.109)	(-3.624)	(1.573)
Employ	-0.000	-0.000***	0.000
	(-0.524)	(-4.278)	(0.917)
Industry	*Yes*	*Yes*	*Yes*
Year	*Yes*	*Yes*	*Yes*
Province	*Yes*	*Yes*	*Yes*
_cons	-0.196	-0.033	-13.085***
	(-1.222)	(-1.113)	(-13.923)
N	34271	34271	34271
R2_a	0.127	0.184	0.311
Sobel Z		5.957^{***}	9.752^{***}
Proportion		15.683%	13.264%

(2) Enhancing Firm Reputation

Applying the same approach, we examine the mediating role of firm reputation, with the outcomes summarized in Table 5. Column (1) reports that the coefficient of *AI_utilize* is significantly positive at the 1% level, showing that AI adoption markedly enhances corporate reputation. After introducing reputation into the regression framework, Columns (2) and (3) indicate that the coefficients of *Reputation* remain strongly positive, implying that reputation contributes to improvements in both financial and environmental performance. At the same time, although the coefficients of *AI_utilize* are still significant, their magnitudes are reduced compared with the baseline, suggesting that reputation acts as a partial mediator. The Sobel Z statistics, 9.685 and 9.236, are both significant at the 1% level. Overall, AI adoption helps firms gain media visibility and strengthen reputation, which in turn increases resource access and enhances dual performance. These findings validate Hypothesis 3.

Table 5. Regression Results-Mediating Effect of Firm Reputation

	(1)	(2)	(3)
	Reputation	*ROA*	*EP*
Reputation		0.007***	0.111***
		(8.160)	(7.175)
AI_utilize	0.158***	0.003***	0.259***
	(4.341)	(3.793)	(2.907)
Size	0.410***	-0.002**	0.543***
	(23.542)	(-2.263)	(13.814)
Cashflow	1.173***	0.349***	0.931***
	(5.739)	(7.043)	(2.863)
INV	-0.113	0.016	0.108
	(-0.600)	(1.546)	(0.402)
Growth	0.000***	-0.000	-0.000***
	(3.183)	(-0.471)	(-7.796)
Board	0.224***	-0.002	0.514***
	(2.902)	(-0.795)	(4.457)
Indep	0.009***	-0.000**	0.003
	(3.541)	(-2.089)	(0.569)
Dual	0.111***	0.004**	-0.189***
	(7.618)	(2.480)	(-5.086)
Top10	0.194**	0.088***	0.287**
	(2.711)	(13.657)	(2.483)
Balance	0.110**	-0.006*	-0.070
	(2.606)	(-1.873)	(-1.150)
FirmAge	-0.173***	-0.005***	0.128
	(-4.337)	(-2.976)	(1.714)
Employ	0.000***	-0.000***	0.000
	(3.098)	(-4.781)	(0.721)
Industry	*Yes*	*Yes*	*Yes*
Year	*Yes*	*Yes*	*Yes*
Province	*Yes*	*Yes*	*Yes*
_cons	-4.991***	0.003	-12.560***
	(-12.898)	(0.104)	(-13.731)

N	34271	34271	34271
R2_a	0.503	0.192	0.313
Sobel Z		9.685***	9.236***
Proportion		42.352%	11.436%

(3) Strengthening Strategic Cooperation

We further examine the mediating function of strategic cooperation using the same procedure, with the outcomes presented in Table 6. Column (1) demonstrates that the coefficient of *AI_utilize* is significantly positive at the 1% level, implying that AI adoption effectively boosts firms' engagement in strategic alliances. When *Alliance* is added to the regression framework, Columns (2) and (3) reveal that its coefficients are both significantly positive at the 1% level, indicating that stronger cooperation meaningfully improves both financial and environmental outcomes. Although the coefficients of *AI_utilize* remain positive and significant, their magnitudes decrease relative to the baseline, suggesting that strategic cooperation plays a partial mediating role in the link between AI applications and performance. The Sobel Z statistics, 2.684 and 9.391, are also significant at the 1% level. Overall, AI use strengthens firms' capacity to form alliances, leverage complementary resources, and establish collaborative partnerships, thereby advancing dual performance. These results lend support to Hypothesis 4.

Table 6. Regression Results-Mediating Effect of Strategic Cooperation

	(1) *Alliance*	(2) *ROA*	(3) *EP*
Alliance		0.003*	0.057*
		(1.730)	(1.841)
AI_utilize	0.082***	0.004***	0.272***
	(8.562)	(6.788)	(3.222)
Size	0.015**	0.001	0.588***
	(2.556)	(1.656)	(13.898)
Cashflow	-0.083**	0.358***	1.066***
	(-2.600)	(7.009)	(3.309)
INV	-0.072	0.016	0.099
	(-1.128)	(1.562)	(0.390)
Growth	-0.000***	0.000	-0.000***
	(-9.055)	(0.124)	(-7.200)
Board	-0.018	-0.000	0.540***
	(-0.572)	(-0.138)	(4.505)
Indep	-0.002**	-0.000	0.004
	(-2.690)	(-1.457)	(0.801)
Dual	0.016	0.004***	-0.178***
	(0.975)	(2.907)	(-4.662)
Top10	-0.013	0.089***	0.309**
	(-0.415)	(13.711)	(2.736)
Balance	0.005	-0.005	-0.058
	(0.286)	(-1.560)	(-0.977)
FirmAge	-0.058***	-0.006***	0.112

	(-7.508)	(-3.435)	(1.506)
Employ	-0.000*	-0.000***	0.000
	(-1.943)	(-4.305)	(0.918)
Industry	*Yes*	*Yes*	*Yes*
Year	*Yes*	*Yes*	*Yes*
Province	*Yes*	*Yes*	*Yes*
_cons	0.422***	-0.036	-13.138***
	(3.452)	(-1.189)	(-13.903)
N	34271	34271	34271
R2_a	0.095	0.184	0.310
Sobel Z		2.684***	9.391***
Proportion		9.474%	12.294%

4.4 Moderation Effect Tests

To evaluate Hypothesis H5, we introduce the interaction term *AI_utilize* × *High_edu* into Model (2) to test whether the proportion of highly educated employees moderates the link between AI adoption and firm performance. The regression outcomes, shown in Columns (1)–(2) of Table 7, reveal that the interaction coefficients are significantly positive at the 10% and 1% levels, respectively. These findings suggest that a higher share of highly educated human capital amplifies the beneficial effect of AI applications on both financial and environmental performance.

To test Hypothesis H6, we include the interaction term between *AI_utilize* and *Regulation* in Model (2) to examine the moderating effect of regional environmental regulation. The regression results are shown in columns (3)–(4) of Table 7. In column (3), the coefficient of *AI_utilize* × *Regulation* is not significant, while in column (4) it is significantly positive at the 1% level. This suggests that regional environmental regulation significantly strengthens the positive relationship between AI applications and environmental performance, but its moderating effect on financial performance is not significant.

Table 7. Regression Results-Moderating Effects of Highly Educated Human Capital Structure and Regional Environmental Regulation

	(1)	(2)	(3)	(4)
	ROA	*EP*	*ROA*	*EP*
AI_utilize	-0.002	0.001	0.005	-0.368
	(-0.829)	(0.021)	(1.530)	(-1.432)
High_edu	0.000***	-0.003***		
	(3.632)	(-3.669)		
*AI_utilize * High_edu*	0.000*	0.005***		
	(2.082)	(3.701)		
Regulation			1.479***	12.295*
			(5.840)	(2.080)
*AI_utilize * Regulation*			-0.148	96.926***
			(-0.248)	(3.624)
Size	0.001	0.591***	0.001	0.589***

	(1.374)	(14.004)	(1.687)	(13.967)
Cashflow	0.360***	1.030***	0.357***	1.058***
	(7.104)	(3.266)	(7.017)	(3.235)
INV	0.016	0.088	0.015	0.095
	(1.516)	(0.346)	(1.527)	(0.375)
Growth	0.000	-0.000***	-0.000	-0.000***
	(0.008)	(-7.502)	(-0.132)	(-7.497)
Board	-0.001	0.545***	-0.001	0.532***
	(-0.303)	(4.605)	(-0.210)	(4.412)
Indep	-0.000	0.004	-0.000	0.004
	(-1.588)	(0.826)	(-1.552)	(0.730)
Dual	0.004***	-0.177***	0.004***	-0.177***
	(2.940)	(-4.649)	(2.949)	(-4.798)
Top10	0.089***	0.301**	0.089***	0.312**
	(13.619)	(2.683)	(13.789)	(2.711)
Balance	-0.006	-0.056	-0.005	-0.058
	(-1.711)	(-0.950)	(-1.552)	(-0.972)
FirmAge	-0.006***	0.104	-0.006***	0.109
	(-3.697)	(1.405)	(-3.610)	(1.471)
Employ	-0.000***	0.000	-0.000***	0.000
	(-4.319)	(0.898)	(-4.281)	(0.907)
Industry	*Yes*	*Yes*	*Yes*	*Yes*
Year	*Yes*	*Yes*	*Yes*	*Yes*
Province	*Yes*	*Yes*	*Yes*	*Yes*
_cons	-0.034	-13.071***	-0.044	-13.180***
	(-1.112)	(-13.723)	(-1.453)	(-13.832)
N	34271	34271	34271	34271
R2_a	0.185	0.311	0.184	0.312

4.5 Robustness and Endogeneity Tests

(1) Robustness Tests with Alternative Measures and Lagged Variables

To further examine the robustness of the results, we re-estimate the models by changing the measurement of the dependent variables, financial performance and environmental performance. For financial performance, we replace *ROA* with return on equity (*ROE*), *Tobin Q*, and the price-to-book ratio (*PB*). For environmental performance, we construct an alternative index (*EP2*) based on firms' disclosure in six areas: air emission reduction, wastewater reduction, dust reduction, solid waste utilization and disposal, noise and light control, and adoption of cleaner production. Each item is scored as 0 (no disclosure), 1 (qualitative disclosure), or 2 (quantitative disclosure), and the total score is used as the comprehensive measure of environmental governance performance.

Table 8 presents the regression outcomes. Columns (1)–(3) display the estimates for financial performance, while Column (4) reports the result for environmental performance. All coefficients are significantly positive, aligning with the baseline analysis. Furthermore, to address potential reverse causality, *AI_utilize* is lagged by one period. The results in Columns (5)–(6) remain robust and consistent with the baseline findings.

Table 8. Regression Results-Robustness Tests with Alternative Measures and Lagged Variables

	(1)	(2)	(3)	(4)	(5)	(6)
	ROE	*Tobin Q*	*PB*	*EP2*	*ROA*	*EP*
AI_utilize	0.020**	0.135***	0.107**	0.171*		
	(2.647)	(3.374)	(2.701)	(1.905)		
L.AI_utilize					0.004***	0.286***
					(4.223)	(4.340)
Size	0.021	-0.514***	-1.904***	0.624***	0.001	0.605***
	(1.504)	(-10.856)	(-7.114)	(8.592)	(1.338)	(14.524)
Cashflow	0.828***	1.321**	-4.995*	1.487***	0.378***	1.098**
	(3.582)	(2.478)	(-2.016)	(3.945)	(7.819)	(2.582)
INV	0.143*	-0.219	-1.458*	0.141	0.014	0.096
	(1.855)	(-0.753)	(-1.734)	(0.468)	(1.391)	(0.304)
Growth	0.000	-0.000	0.000	-0.000***	-0.000	-0.002***
	(0.558)	(-0.566)	(1.459)	(-3.516)	(-0.642)	(-5.454)
Board	-0.105**	0.064	1.272**	0.538***	-0.000	0.592***
	(-2.310)	(0.552)	(2.392)	(3.535)	(-0.025)	(4.022)
Indep	-0.006	0.012***	0.067***	-0.000	-0.000	0.005
	(-1.638)	(4.002)	(7.251)	(-0.088)	(-1.235)	(0.899)
Dual	0.026	-0.034	0.532*	-0.137***	0.004**	-0.205***
	(1.131)	(-0.785)	(1.958)	(-3.374)	(2.134)	(-4.060)
Top10	0.150*	-0.841***	-2.440**	0.741***	0.073***	0.400***
	(1.862)	(-3.164)	(-2.129)	(3.665)	(10.216)	(3.169)
Balance	-0.041	0.043	0.643	-0.077	-0.005	-0.062
	(-0.998)	(0.387)	(0.803)	(-1.124)	(-1.417)	(-0.945)
FirmAge	0.014	0.309***	1.132***	0.196*	-0.005***	0.119
	(0.485)	(5.596)	(3.109)	(2.040)	(-3.188)	(1.361)
Employ	-0.000	0.000***	0.000**	0.000	-0.000***	0.000
	(-0.666)	(3.526)	(2.786)	(1.613)	(-3.764)	(0.854)
Industry	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Province	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
_cons	-0.188	12.414***	39.137***	-14.030***	-0.027	-13.684***
	(-0.400)	(9.721)	(6.787)	(-6.993)	(-0.851)	(-14.014)
N	34271	34271	34271	34271	26721	26721
R2_a	0.002	0.103	0.021	0.293	0.198	0.313

(2) Change Model

According to signaling theory, changes in AI application are more likely to be viewed as signals that predict firm prospects. When AI utilization changes only slightly, it is difficult to generate clear marginal benefits (Chen et al., 2024). To further address potential endogeneity concerns, we adopt a change model. Specifically, we regress changes in firm performance on changes in AI utilization to test whether improvements in dual performance are driven by changes in AI adoption. The model is shown in equation (15):

$$\Delta ROA_{i,t}/\Delta EP_{i,t} = \alpha_0 \Delta AI\_utilize_{i,t} + \Sigma Controls_{i,t} + \Sigma Year + \Sigma Industry + \Sigma Province + \varepsilon_{i,t} \quad (15)$$

The regression results are reported in columns (1)–(2) of Table 9, and they remain consistent with the main hypotheses.

Moreover, since *EP* is a discrete non-negative integer variable and some firms report zero values, we follow Jiang and Yuan (2018) and use Poisson regression as a robustness check. The results are reported in column (3) of Table 9. The coefficient of *AI_utilize* remains significantly positive at the 1% level, consistent with the baseline results, confirming the robustness of our findings.

Table 9. Regression Results-Robustness Analysis with the Change Model

	(1)	(2)	(3)
	D.ROA	*D.EP*	*EP*
D.AI_utilize	0.004*	0.208***	
	(1.733)	(4.700)	
AI_utilize			0.190***
			(5.756)
Size	-0.004***	0.071**	0.313***
	(-2.916)	(2.558)	(35.289)
Cashflow	0.201***	0.291*	0.680***
	(25.836)	(1.731)	(6.168)
INV	0.015*	0.117	0.279**
	(1.839)	(0.653)	(2.373)
Growth	0.000**	0.000	-0.002
	(2.025)	(0.221)	(-1.427)
Board	-0.008	-0.015	0.300***
	(-1.545)	(-0.126)	(4.838)
Indep	-0.000	0.005	0.000
	(-0.680)	(1.567)	(0.101)
Dual	-0.001	-0.040	-0.112***
	(-0.489)	(-1.107)	(-5.119)
Top10	0.015**	0.461***	0.137*
	(2.228)	(3.156)	(1.908)
Balance	-0.006	-0.023	-0.041
	(-1.619)	(-0.310)	(-1.089)
FirmAge	-0.005	0.016	0.033
	(-0.619)	(0.094)	(0.895)
Employ	-0.000	-0.000	-0.000***
	(-0.825)	(-0.647)	(-4.901)
Industry	Yes	Yes	*Yes*
Year	Yes	Yes	*Yes*
Province	Yes	Yes	*Yes*
_cons	0.099***	-1.748**	-8.326***
	(2.834)	(-2.316)	(-31.022)

N	26721	26721	34271
R2_a	-0.151	-0.164	/

(3) Propensity Score Matching

To mitigate possible self-selection bias stemming from firms' financial and governance traits, we apply propensity score matching (PSM). Companies that adopt AI are classified as the treatment group, whereas those without AI adoption serve as the control group. We use the control variables from the baseline regression—*Size*, *Cashflow*, *INV*, *Growth*, *Dual*, *Top10*, *Balance*, *FirmAge* and *Employ*—to conduct one-to-five nearest neighbor matching. This results in 5,771 matched samples. Because the treatment group is relatively small, one-to-five matching allows for more precise matches and mitigates self-selection bias.

We then re-estimate the baseline models using the matched samples. Columns (1) – (2) of Table 10 present the results for financial and environmental performance, showing that the coefficients of AI_utilize remain significantly positive at the 1% level, consistent with earlier findings. Columns (3) – (4) report the outcomes using kernel matching, which further confirm the main conclusions.

Table 10. Regression Results-Propensity Score Matching

	1:5 neighbor		kernel	
	ROA	*EP*	*ROA*	*EP*
AI_utilize	0.008***	0.364***	0.004***	0.004***
	(4.547)	(4.306)	(6.442)	(6.442)
Size	0.005***	0.603***	0.001	0.001
	(3.673)	(18.278)	(1.625)	(1.625)
Cashflow	0.356***	1.181***	0.366***	0.366***
	(11.227)	(3.328)	(7.481)	(7.481)
INV	0.004	0.399**	0.026**	0.026**
	(0.264)	(2.098)	(2.474)	(2.474)
Growth	0.006**	-0.025***	0.004***	0.004***
	(2.558)	(-2.976)	(6.050)	(6.050)
Board	-0.003	0.413***	0.000	0.000
	(-0.315)	(3.557)	(0.078)	(0.078)
Indep	-0.000	-0.005	-0.000	-0.000
	(-1.601)	(-0.859)	(-1.380)	(-1.380)
Dual	0.005*	-0.124*	0.004**	0.004**
	(1.982)	(-1.795)	(2.695)	(2.695)
Top10	0.120***	0.447**	0.089***	0.089***
	(9.310)	(2.574)	(13.659)	(13.659)
Balance	-0.006	0.071	-0.005	-0.005
	(-1.582)	(1.204)	(-1.696)	(-1.696)
FirmAge	-0.005	0.204**	-0.006***	-0.006***
	(-1.230)	(2.217)	(-3.946)	(-3.946)
Employ	-0.000***	0.000***	-0.000***	-0.000***
	(-4.049)	(4.222)	(-4.319)	(-4.319)
Industry	*Yes*	*Yes*	*Yes*	*Yes*
Year	*Yes*	*Yes*	*Yes*	*Yes*

Province	*Yes*	*Yes*	*Yes*	*Yes*
_cons	-0.122***	-13.320***	-0.034	-0.034
	(-3.105)	(-16.905)	(-1.195)	(-1.195)
N	5771	5771	33591	33591
R2_a	0.181	0.286	0.187	0.187

4. Placebo Test

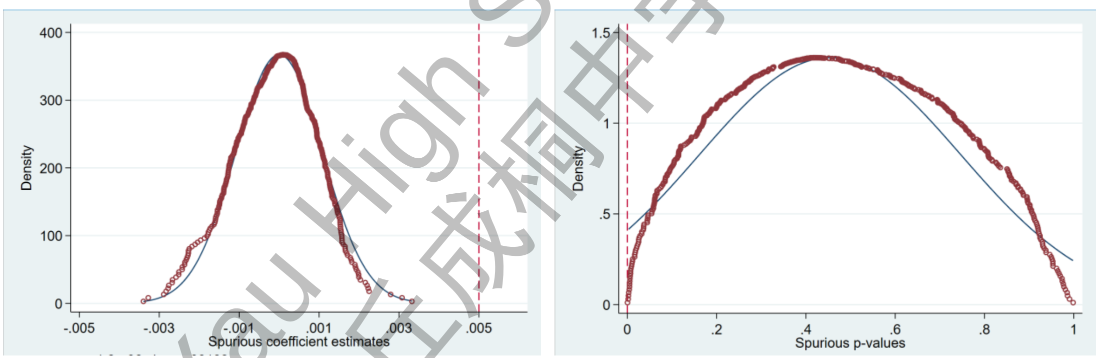
Finally, the association observed between AI adoption and firms' dual performance might stem from time effects or random noise. To exclude this possibility, we perform a placebo test by constructing a pseudo-AI variable, following a three-step procedure:

1.Randomly assign a pseudo *AI_utilize* variable to firms.

2.Replace the real *AI_utilize* variable with the pseudo variable and re-estimate model (1).

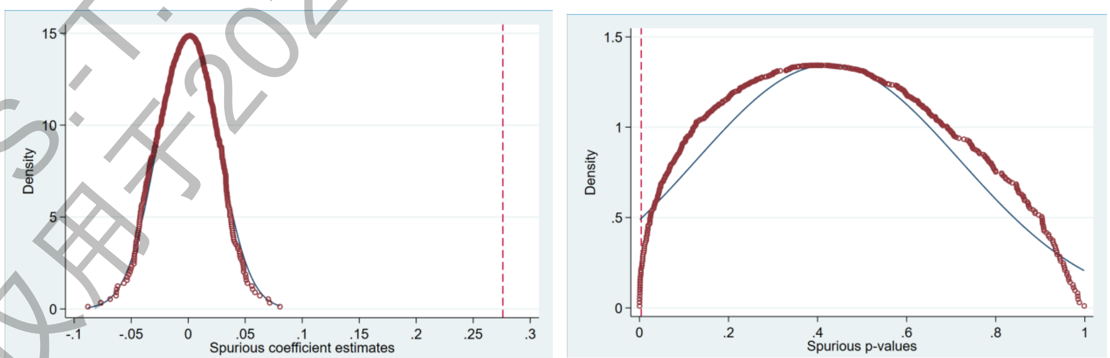
3.Repeat steps 1 and 2 five hundred times.

Figures 2 and 3 show the placebo test results for financial and environmental performance, respectively. Panel (a) shows the distribution of estimated coefficients, and panel (b) shows the distribution of p-values. The estimated coefficients from the placebo regressions are symmetrically distributed around zero, while the true coefficients from the main models are far outside this distribution. Moreover, most p-values from the placebo regressions are greater than 0.01, much larger than the significance levels in the main models. These findings confirm that the observed positive impact of AI utilization on dual performance is not driven by random noise or spurious correlation.



（a） （b）

Figure 2. Placebo Test of *AI_utilize* on *ROA*



（a） （b）

Figure 3. Placebo Test of *AI_utilize* on *EP*

4.6 Extension Analysis

(1) Heterogeneity Analysis

The ownership nature shapes firms' preferences in applying AI toward different goals. For private firms, external financing constraints and barriers to resource acquisition make them more dependent on new technologies to improve operational efficiency and optimize resource allocation (Faccio et al., 2016). AI helps firms break limits in information processing and decision-making, thereby easing survival pressure and improving financial performance. At the same time, private firms face more direct market competition and institutional constraints. To reduce environmental risks and compliance costs, they also tend to use AI technologies to seek efficient environmental governance solutions, thus enhancing environmental performance (Small et al., 2022).

In contrast, state-owned enterprises (SOEs) enjoy a more stable resource supply under institutional arrangements. However, their managers often carry both business and administrative responsibilities. As a result, AI applications are more likely to serve public governance goals, especially the improvement of environmental performance. On financial performance, the large-scale and rigid operating mechanisms of SOEs reduce the acceptance of new technologies within the organization. Thus, the marginal effect of AI in improving financial returns is not significant (Liang and Renneboog, 2017).

Furthermore, AI expands firms' innovation boundaries, improves firm reputation, and strengthens strategic cooperation, bringing additional resources. The ownership nature determines how firms absorb and use these resources. Private firms, driven by strong profit orientation, are more likely to convert additional resources into profitability to enhance competitiveness. At the same time, under regulatory and compliance pressure, they allocate part of the resources to environmental governance to reduce institutional risks (Wang et al., 2016). SOEs, however, due to policy goals and social responsibility orientation, tend to focus new resources on environmental performance improvement, with limited effects on financial returns. Therefore, firms with different ownership natures follow differentiated paths in AI empowerment, leading to divergent effects on financial and environmental performance.

Columns (1) and (3) of Table 11 show that, in the private firm sample, the regression coefficient of *AI_utilize* on *ROA* is 0.005 and significant at the 1% level, indicating that private firms can more effectively convert AI-related resources into profitability. At the same time, the coefficient of *AI_utilize* on *EP* is 0.277 and significant at the 5% level, suggesting that private firms also use AI to optimize environmental management under compliance pressure. Columns (2) and (4) of Table 11 show that, in the SOE sample, the coefficient of *AI_utilize* on *EP* is 0.015 and significant at the 1% level, while the coefficient on *ROA* is not significant. This result confirms that SOEs prioritize environmental governance and social responsibility in AI applications. These findings suggest that ownership nature not only influences the direction of AI application but also shapes differentiated outcomes at the performance level.

Table 11. Regression Results-Heterogeneity Analysis by Ownership Nature

	(1)	(2)	(3)	(4)
	SOE=0	*SOE=1*	*SOE=0*	*SOE=1*
	ROA	*ROA*	*EP*	*EP*
AI_utilize	0.005***	0.002	0.277**	0.328***
	(8.779)	(0.852)	(2.806)	(6.486)

Size	0.005***	0.000	0.482***	0.614***
	(6.106)	(0.319)	(8.415)	(12.184)
Cashflow	0.391***	0.279***	1.043***	1.377**
	(9.125)	(4.295)	(4.761)	(2.146)
INV	0.016*	0.013	0.021	0.003
	(1.922)	(0.881)	(0.096)	(0.006)
Growth	-0.000	-0.000	-0.002***	-0.000***
	(-1.206)	(-0.201)	(-5.397)	(-9.394)
Board	0.003	0.005	0.316**	0.468*
	(0.667)	(0.884)	(2.236)	(1.925)
Indep	-0.000	-0.000	-0.004	0.007
	(-0.209)	(-1.640)	(-0.745)	(0.836)
Dual	0.003**	0.002	-0.118**	-0.111**
	(2.116)	(1.037)	(-2.535)	(-2.790)
Top10	0.109***	0.062***	0.209	0.202
	(14.432)	(7.332)	(1.035)	(0.723)
Balance	-0.004	-0.013***	-0.022	0.107
	(-1.099)	(-5.996)	(-0.465)	(0.897)
FirmAge	-0.005**	-0.004	0.088*	-0.082
	(-2.725)	(-1.151)	(1.762)	(-0.513)
Employ	-0.000***	-0.000**	0.000***	-0.000
	(-4.100)	(-2.767)	(5.215)	(-0.522)
Industry	*Yes*	*Yes*	*Yes*	*Yes*
Year	*Yes*	*Yes*	*Yes*	*Yes*
Province	*Yes*	*Yes*	*Yes*	*Yes*
_cons	-0.135***	-0.011	-9.942***	-13.135***
	(-4.835)	(-0.326)	(-7.083)	(-11.983)
Prob>Chi^2	0.003***		0.240	
N	21377	12893	21377	12893
R2_a	0.210	0.144	0.275	0.352

The role of whether a firm is a high-tech enterprise may also significantly influence the effects of AI applications on financial and environmental performance. AI encompasses diverse technologies and application scenarios, and different types of AI address different firm problems. High-tech firms, with advantages in knowledge structure and R&D capacity, can select appropriate technologies tailored to their development needs, thereby enhancing dual performance. In contrast, non-high-tech firms are constrained by limited knowledge and capabilities. Even with the same technology, they may fail to fully utilize it. High-tech firms, supported by specialized human capital and abundant technological reserves, can embed AI systems more efficiently, resulting in stronger performance improvements.

Environmental governance is often complex and resource-intensive. High-tech firms can use AI to identify key pain points, achieve more precise resource allocation, improve environmental compliance, and build social reputation for long-term advantage. Non-high-tech firms, in contrast, often respond passively in environmental governance. Even when temporarily adopting AI, its value is difficult to realize.

Columns (2) and (4) of Table 12 show that, in the high-tech firm sample, the coefficient of *AI_utilize* on *ROA* is 0.005 and significant at the 1% level, indicating that high-tech firms can more efficiently convert AI into profitability. The coefficient on *EP* is 0.317 and significant at the 5% level, suggesting that high-tech firms not only improve financial performance through AI but also achieve notable outcomes in environmental governance. Columns (1) and (3) of Table 12 show that, in the non-high-tech firm sample, the coefficients of *AI_utilize* on both *ROA* and *EP* are not significant, indicating that the value of AI has not been fully realized. Overall, high-tech firms, with stronger technological reserves and knowledge advantages, can more effectively absorb and utilize AI resources, thereby exhibiting more significant improvements in dual performance.

Table 12. Regression Results-Heterogeneity Analysis by High-Tech Enterprise Status

	(1)	(2)	(3)	(4)
	High_tech=0	*High_tech =1*	*High_tech =0*	*High_tech =1*
	ROA	*ROA*	*EP*	*EP*
AI_utilize	-0.002	0.005***	0.057	0.317**
	(-0.416)	(5.305)	(0.351)	(3.272)
Size	0.002	0.001*	0.556***	0.597***
	(1.451)	(2.177)	(10.337)	(21.082)
Cashflow	0.277***	0.420***	0.443	1.561***
	(4.916)	(5.505)	(1.628)	(9.390)
INV	-0.003	0.038*	-0.235	0.565*
	(-0.255)	(2.216)	(-0.918)	(2.660)
Growth	-0.000**	-0.000	-0.000***	-0.002
	(-2.419)	(-0.807)	(-7.808)	(-1.653)
Board	0.002	-0.002	0.484*	0.596***
	(0.466)	(-1.304)	(1.737)	(7.279)
Indep	-0.000	-0.000	0.014**	-0.003*
	(-0.408)	(-1.683)	(2.448)	(-2.372)
Dual	0.003	0.006**	-0.199***	-0.153**
	(0.793)	(3.600)	(-3.755)	(-3.219)
Top10	0.083***	0.095***	-0.034	0.649***
	(9.573)	(9.309)	(-0.152)	(4.910)
Balance	-0.015***	-0.000	0.070	-0.124
	(-3.639)	(-0.118)	(0.933)	(-1.862)
FirmAge	-0.002	-0.009***	-0.101	0.199*
	(-0.596)	(-5.086)	(-0.749)	(2.256)
Employ	-0.000***	-0.000*	0.000	0.000*
	(-3.391)	(-2.535)	(0.447)	(2.335)
Industry	*Yes*	*Yes*	*Yes*	*Yes*
Year	*Yes*	*Yes*	*Yes*	*Yes*
Province	*Yes*	*Yes*	*Yes*	*Yes*
_cons	-0.074	-0.026	-12.108***	-13.490***
	(-1.373)	(-0.892)	(-8.081)	(-24.454)
Prob>Chi²	0.005***		0.005***	

N	13839	20432	13839	20432
$R2\_a$	0.164	0.210	0.333	0.308

(2) Effects of Different Types of AI Applications on Dual Performance

This study classifies AI technologies into four categories: knowledge representation and reasoning (*KRR*), computer vision (*CV*), natural language processing (*NLP*), and machine learning (*ML*). To measure firms' application levels of these four types of AI technologies, we calculate the frequency of related keywords in annual reports and then apply a log transformation after adding one, to mitigate the influence of extreme values and maintain a reasonable distribution. Table 13 reports the regression results of different AI applications on financial performance and environmental performance.

From the regression results, column (1) of Table 13 shows that the coefficient of *KRR* on *ROA* is 0.009 and significant at the 1% level, indicating that *KRR* enhances firms' operational efficiency and financial performance through knowledge modeling and rule-based reasoning. Column (2) shows that the coefficient of *CV* on *ROA* is 0.003 and significant at the 5% level, suggesting that computer vision improves profitability by supporting production inspection and process optimization. Columns (3) and (4) report the effects of *NLP* and *ML* on *ROA*. The coefficients are 0.002 and 0.004, respectively, but neither reaches statistical significance, indicating that these two technologies have not yet shown stable effects on financial performance.

For environmental performance, columns (5) to (8) show that the coefficients of the four AI technologies are 0.306, 0.303, 0.868, and 0.654, respectively, and all are significant at the 1% level. This suggests that all four AI technologies significantly improve firms' environmental governance capabilities.

The underlying reason may be that different types of AI technologies essentially provide extensions of external knowledge and capabilities, but the effectiveness of transformation depends on firms' internal knowledge structures and absorptive capacities. In terms of financial performance, *KRR* and *CV* are more closely related to production and operational processes and are easier to integrate with existing business activities, thus achieving higher efficiency in generating financial returns. In contrast, *NLP* and *ML* require higher learning costs and knowledge accumulation, making it difficult to deliver stable financial improvement in the short term. This finding is consistent with recent evidence that digital capabilities need to go through organizational absorption and transformation pathways to achieve sustainable performance gains (Hanelt et al., 2021).

In contrast, for environmental performance, external compliance pressure and social responsibility provide clear goals for AI application. Each type of AI technology contributes to solving environmental problems in different dimensions: *KRR* reduces risks through standardized governance, *CV* enhances control through intuitive monitoring, *NLP* improves compliance through better policy understanding and external communication, and *ML* optimizes resource allocation through complex data analysis. Cross-country evidence also shows that when facing environmental challenges, firms are more likely to integrate digital technologies and external knowledge to meet regulatory and stakeholder expectations (Zahoor and Lew, 2022). Therefore, different AI technologies not only expand the resource boundaries available to firms but also exhibit heterogeneous effects on financial and environmental performance.

Table 13. Regression Results-Analysis of Different Types of AI Applications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)

	ROA	ROA	ROA	ROA	EP	EP	EP	EP
KRR	0.009***				0.306***			
	(3.217)				(4.637)			
CV		0.003**				0.303***		
		(2.501)				(9.363)		
NLP			0.002				0.868***	
			(0.249)				(3.685)	
ML				0.004				0.654***
				(1.242)				(9.190)
Size	0.001***	0.001***	0.001***	0.001***	0.588***	0.589***	0.588***	0.588***
	(3.374)	(3.439)	(3.406)	(3.402)	(65.389)	(65.617)	(65.398)	(65.460)
Cashflow	0.357***	0.357***	0.357***	0.357***	1.051***	1.054***	1.040***	1.060***
	(66.693)	(66.675)	(66.646)	(66.663)	(8.272)	(8.306)	(8.184)	(8.351)
INV	0.016***	0.015***	0.015***	0.015***	0.101	0.093	0.104	0.099
	(3.998)	(3.970)	(3.995)	(3.991)	(1.103)	(1.011)	(1.128)	(1.078)
Growth	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(-0.001)	(-0.004)	(-0.000)	(-0.002)	(-0.755)	(-0.769)	(-0.755)	(-0.766)
Board	-0.000	-0.001	-0.001	-0.000	0.542***	0.533***	0.533***	0.543***
	(-0.161)	(-0.231)	(-0.216)	(-0.197)	(9.363)	(9.226)	(9.213)	(9.399)
Indep	-0.000**	-0.000**	-0.000**	-0.000**	0.004*	0.004*	0.004*	0.004**
	(-2.425)	(-2.409)	(-2.417)	(-2.401)	(1.843)	(1.882)	(1.833)	(1.965)
Dual	0.005***	0.004***	0.005***	0.005***	-0.171***	-0.176***	-0.172***	-0.174***
	(5.106)	(5.050)	(5.121)	(5.103)	(-8.144)	(-8.397)	(-8.180)	(-8.289)
Top10	0.089***	0.089***	0.089***	0.089***	0.296***	0.310***	0.298***	0.294***
	(33.462)	(33.495)	(33.437)	(33.437)	(4.701)	(4.923)	(4.729)	(4.672)
Balance	-0.005***	-0.005***	-0.005***	-0.005***	-0.055*	-0.056*	-0.056*	-0.059*
	(-3.766)	(-3.767)	(-3.757)	(-3.771)	(-1.708)	(-1.740)	(-1.727)	(-1.817)
FirmAge	-0.006***	-0.006***	-0.006***	-0.006***	0.095***	0.105***	0.092***	0.104***
	(-4.804)	(-4.749)	(-4.869)	(-4.816)	(3.132)	(3.469)	(3.044)	(3.409)
Employ	-0.000***	-0.000***	-0.000***	-0.000***	0.000***	0.000***	0.000***	0.000***
	(-7.540)	(-7.576)	(-7.569)	(-7.549)	(4.194)	(4.126)	(4.125)	(4.284)
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
_cons	-0.033***	-0.034***	-0.033***	-0.033***	-13.04***	-13.10***	-13.01***	-13.00***
	(-3.226)	(-3.272)	(-3.184)	(-3.217)	(-53.523)	(-53.814)	(-53.397)	(-53.722)
N	34271	34271	34271	34271	34271	34271	34271	34271
R2_a	0.183	0.183	0.183	0.183	0.309	0.310	0.309	0.310

(3) The Impact of AI Applications on Sustainable Development Performance

The 20th National Congress of the Communist Party of China emphasized that pursuing green and low-carbon development is crucial for achieving high-quality growth. In the same vein, the 2024 *Opinions of the CPC Central Committee and the State Council on Accelerating the Comprehensive Green Transformation of Economic and Social Development* underline the importance of combining industrial digitalization and intelligentization with green transition, expanding the application of AI and related technologies, and utilizing digital innovation to power sustainable transformation. Against this policy background, AI is regarded as an important tool for helping firms balance financial performance and environmental performance, thereby improving sustainable development performance.

Following Lunnan and Haugland (2008), this paper constructs a composite indicator of sustainable development performance (SusDev) using the standardized results of firms' financial performance and environmental performance. The calculation formula is:

$$SusDev = \left[(1 - |ROA - EP|) \times \sqrt{ROA \times EP}\right]/1$$

In this formula, *ROA* and *EP* represent the standardized variables. The value of the *SusDev* indicator is constrained to a range between 0 and 1. This indicator reflects the degree of coordination between economic benefits and environmental responsibility, and effectively captures the impact of AI applications on the balance of dual goals.

Table 14 presents the regression outcomes of *AI_utilize* on *SusDev*. For the overall sample, the coefficient is 0.001 and statistically insignificant, implying that AI has only a limited role in balancing dual objectives across firms. Subsample results reveal that within high-pollution sectors, the coefficient reaches 0.013 and is significant at the 5% level, showing that AI adoption notably enhances sustainable development in these industries. By contrast, in non-high-pollution sectors, the coefficient is 0.002 and remains insignificant. These results imply that the value of AI applications is better realized in industries with greater resource constraints and external pressure. In particular, firms in high-pollution industries can rely on AI to ease transformation challenges.

Table 14. The Impact of AI Applications on Sustainable Development Performance

	(1)	(2)	(3)
		Pollution =1	*Pollution =0*
	SusDev	*SusDev*	*SusDev*
AI_utilize	0.001	0.013**	0.002
	(0.299)	(3.054)	(0.286)
Size	0.023***	0.022***	0.024***
	(21.752)	(6.288)	(25.681)
Cashflow	0.230***	0.298***	0.200***
	(7.370)	(10.395)	(5.980)
INV	0.027*	0.064*	0.016
	(1.743)	(2.302)	(0.858)
Growth	-0.000***	-0.000***	-0.000***
	(-16.953)	(-15.085)	(-15.947)
Board	0.009	0.029	0.000
	(0.963)	(2.083)	(0.054)
Indep	-0.000	0.000	-0.000
	(-0.349)	(0.965)	(-1.418)
Dual	0.002	0.005*	0.001
	(1.350)	(2.417)	(0.474)
Top10	0.071***	0.075*	0.068***
	(6.360)	(2.375)	(7.003)
Balance	0.005**	0.003	0.004

	(2.174)	(0.332)	(1.116)
FirmAge	-0.012***	-0.022**	-0.008*
	(-3.804)	(-3.024)	(-2.063)
Employ	-0.000***	-0.000**	-0.000**
	(-4.350)	(-4.197)	(-2.263)
Industry	*Yes*	*Yes*	*Yes*
Year	*Yes*	*Yes*	*Yes*
Province	*Yes*	*Yes*	*Yes*
_cons	-0.013	-0.042	-0.004
	(-0.337)	(-0.485)	(-0.123)
N	34271	9943	24328
R2_a	0.206	0.237	0.200

The reason behind this difference is that AI not only provides capabilities for information processing and decision optimization, but also offers critical support for firms under conditions of resource scarcity and increasing institutional pressure. Firms in high-polluting industries face stricter environmental constraints and continuous stakeholder supervision during transformation. As a result, their development strategies pay greater attention to balancing financial performance and environmental performance. On the one hand, while AI improves operational efficiency and profitability, it also helps firms find effective solutions in environmental governance, pollution control, and energy consumption optimization. This enables them to achieve a dynamic balance between economic returns and green responsibility (Li et al., 2020). Through this dual orientation, high-polluting firms can not only relieve external compliance pressure but also enhance social reputation, thereby attracting more external resource support. In contrast, non-high-polluting firms face relatively lower compliance pressure and less urgent demand for environmental performance improvement. Their AI applications focus more on optimizing financial performance, such as cost control and production efficiency. Thus, the marginal impact of AI on overall sustainable development performance is limited (Giacomo and Rizzi, 2021).

5. Discussion

5.1 Research Conclusions

Based on data from China's Shanghai and Shenzhen A-share listed firms during 2009–2023, this paper systematically examines the impact of AI applications on firms' financial performance and environmental performance, focusing on the synergy between efficiency goals and sustainability goals. The results show that AI applications significantly improve firms' dual performance, highlighting their potential and value in balancing financial returns and environmental responsibility.

Mechanism analysis reveals three key pathways through which AI enhances performance: (1) promoting breakthroughs in innovation boundaries, enabling firms to identify and absorb external resources across a broader knowledge scope; (2) improving firm reputation, thereby gaining greater trust and support from capital markets and the public; and (3) strengthening strategic cooperation, helping firms to fill critical resource gaps and generate synergies from resource sharing and technological complementarity.

The moderating effect analysis shows that a higher proportion of highly educated human capital significantly strengthens the positive effect of AI on dual performance, indicating the crucial role of internal talent reserves in transforming AI value. At the same time, stricter regional environmental regulation further amplifies the effect of AI on environmental performance, but its moderating effect on financial performance is not significant.

The extended analysis suggests clear firm heterogeneity in AI application effects. Non-state-owned firms benefit more than state-owned firms, and differences across industries are also evident. Different AI technologies have differentiated effects on performance: NLP and ML have a limited impact on financial performance, while KRR and CV show stronger positive effects. However, differences across AI technologies in environmental performance are not significant. Moreover, in high-polluting firms, AI applications improve sustainable development performance, indicating that AI promotes dual-goal balance and supports green transformation in these firms.

5.2 Research Implications

For firms, it is important to fully recognize the dual value of AI in enhancing financial and environmental performance and incorporate it into long-term strategic planning. Firms should avoid focusing only on efficiency goals and instead seek a balance between financial returns and sustainability. In practice, firms can use AI to expand innovation boundaries, explore cross-industry and cross-domain knowledge integration, and pursue green innovation paths. In terms of reputation management, firms should use AI to improve disclosure quality and customer experience, shaping a trustworthy public image to gain support from markets and society. In strategic cooperation, firms should proactively build alliances with research institutions and supply chain partners to achieve technological complementarity and green synergy.

In addition, firms should optimize their human capital structure by increasing the proportion of highly educated and multidisciplinary talent to strengthen their ability to understand and apply complex AI technologies. They should also adapt to regional environmental regulation by deepening AI applications in emission reduction and energy saving in areas with high environmental pressure. Different types of firms should have different priorities: state-owned firms need to strengthen the balance between efficiency and responsibility, while non-state-owned firms should actively leverage AI to gain resource advantages. High-tech firms can focus on core algorithms and computing power, while non-high-tech firms can improve performance through process management and decision support. High-polluting firms, in particular, need to embed AI into green production and recycling to achieve transformation and upgrading.

For governments, it is necessary to promote wider application of AI in firms through policy guidance and financial support, and to help firms build high-quality talent pools through training programs and industrial incentive policies. Governments should also strengthen the promotion of green values, encouraging firms to integrate environmental goals into their AI applications, especially guiding high-polluting firms to use AI for emission reduction and green transition. At the technical level, governments can support the development of KRR and CV, which contribute more to financial performance, while also promoting the application of NLP and ML in green governance and environmental monitoring. This can better leverage the differentiated advantages of different AI technologies in enhancing dual performance.

5.3 Research Prospects

Future research can be extended in three directions. First, more attention should be given to the differentiated effects of specific AI technologies on firms' dual performance, to reveal technological heterogeneity and provide more concrete guidance for firms to improve performance. Second, AI patent data can be used to measure innovation activities, capturing AI's role in R&D investment, knowledge accumulation, and technology diffusion, and testing its long-term impact on financial and environmental performance. Finally, future research can focus on the application of AI in the green transformation of high-polluting firms, examining its concrete effects in energy saving, emission reduction, cleaner production, and environmental compliance, to reveal how AI provides breakthroughs for resource-intensive firms in achieving a win–win outcome for financial and environmental goals.

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致谢

一、研究背景与指导说明

人工智能在近年来已成为推动企业数字化转型和绿色发展的核心力量。企业是否能够通过人工智能技术实现财务绩效与环境绩效的双赢，是当前学界与实践界共同关注的重要议题。本研究选题正是基于这一现实问题与学术前沿：一方面，人工智能能提升效率与盈利；另一方面，它也可能带来资源配置冲突，对可持续目标产生影响。为此，我们在广泛阅读相关文献的基础上，借鉴南京大学**宋哲**教授的研究，并通过邮件、线下交流等方式与其建立了联系，得到了他的学术启发和无偿指导。**宋哲**教授作为人工智能与企业创新管理领域的专家，在研究方法、理论框架和实证测度等方面给予了我们持续性的帮助。他与团队保持每周约两小时的学术讨论，耐心解答问题并提出改进建议，对研究的规范性和科学性发挥了重要作用。指导全程无偿，纯粹基于学术交流和人才培养目的。研究过程中未有其他人员参与或协助。

二、研究过程与团队分工

研究全过程大致分为五个阶段：选题确定、数据获取、分析建模、实验设计与实施、论文撰写与修改。

1.选题与文献综述

在初始阶段，团队成员广泛阅读人工智能、企业绩效及资源依赖理论相关文献，明确研究问题的现实意义与学术价值。**胡谷蓁溱**主要负责文献整理，形成研究综述，为后续建模提供理论支撑。

2.数据获取与处理

本研究选取 2009－2023 年沪深 A 股上市公司为样本，数据涵盖企业财务与环境信息。数据来源于上市公司年报、CSMAR 与 Wind 数据库。**沈陈菲**主要负责数据下载、清洗与变量构造，例如通过文本分析方法构建人工智能应用指标，完成变量计算与数据预处理。过程中团队遇到的最大困难是文本分析变量的测度问题。通过查阅英文文献、学习 Python 文本挖掘工具包，并在**宋哲**老师的指点下，最终构建了适合本研究的 AI 词典与测度指标。

3.理论分析与模型构建

在宋哲教授指导下，团队基于资源依赖理论提出研究假设，设计实证检验框架。**李怡辰**负责理论分析与假设推导，并协助构建多维度回归模型，确保研究逻辑的完整性。

4.实证分析与实验实施

研究采用文本挖掘、回归模型与稳健性检验等方法，对人工智能应用与企业财务绩效、环境绩效的关系进行系统分析。**沈陈菲**完成了主要的计量计算与统计检验，**胡谷蓁溱**与**李怡辰**参与结果解读，并结合理论框架提出解释。

5.论文撰写与修改

初稿由三位学生分工完成：**沈陈菲**撰写数据与方法部分，**胡谷蓁溱**撰写文献综述与结论，**李怡辰**负责理论分析与全文校对。**宋哲**教授在论文结构、逻辑连贯性及学术表达上提出了修改意见。最终版本经过多轮修改，确保了研究的完整性与规范性。

三、团队成员与指导老师

沈陈菲：南京外国语学校高一学生，研究方向为人工智能应用、企业创新等。

胡谷蓁溱：南京外国语学校高一学生，研究方向为人工智能应用、企业创新等。

李怡辰：南京外国语学校高二学生，研究方向为人工智能应用、企业创新等。

宋哲：南京大学商学院教授、博士生导师，研究方向为创新创业管理、人工智能应用与数据驱动的管理决策优化。2009 年参加工作，2013 年晋升副教授，2016 年晋升教授。