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Artificial Intelligence Applications and Corporate Sustainable Development: An Economic and Environmental Performance Perspective

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ABSTRACT

Against the backdrop of rapid advancements in intelligent technologies and the convergence of China's "dual carbon" strategic goals, how enterprises leverage artificial intelligence to enhance economic and environmental benefits while achieving sustainable development has emerged as a critical research question. This study adopts a dual-perspective approach, examining both financial and environmental performance within the framework of sustainable development. Based on a sample of Chinese A-share listed companies from 2013 to 2023, this study employs a multi-period Difference-in-Differences model to empirically examine the impact of applications of artificial intelligence on corporate sustainable development performance, as well as the underlying mechanisms. The findings reveal: (1) Applications of artificial intelligence enhance both the financial and environmental performance of corporations, thereby improving their overall sustainable development performance. The conclusion has passed a series of robustness tests, including heterogeneity tests and double machine learning. (2) Mechanism analysis reveals that artificial intelligence influences corporate sustainable development performance through green innovation effects, efficiency enhancement effects, and information acquisition effects. The Porter Hypothesis, the Resource-Based View, and the Information Asymmetry Theory, among other theories, have been verified. (3) The promotional effect of artificial intelligence applications on sustainable development performance exhibits heterogeneity. Specifically, the promotional effect is more pronounced in non-heavily polluting enterprises, high-tech enterprises, and enterprises with senior executives possessing environmental protection backgrounds. (4) When enterprises are engaged in intense market competition, the positive relationship between artificial intelligence adoption and sustainability performance strengthens. Our findings offer valuable insights for managers and policymakers aiming to leverage AI for achieving sustainable growth.

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1. Introduction

1.1 Research Background

Global climate change and sustainable development have become the most pressing challenges of our era. As the primary agents of economic activity, enterprises see their development models not only shape their long-term competitiveness but also exert a profound influence on socio-economic prosperity, environmental preservation, and social well-being [1-2]. Sustainable development requires enterprises to balance environmental protection with economic interests, achieving coordinated advancement of economic and ecological benefits [3]. China has proposed the "dual carbon" targets in 2020. Subsequent policies such as the *Corporate Sustainability Disclosure Guidelines—Basic Principles (Trial)* and the Guidelines for *Sustainable Development Reporting of Listed Companies (Trial)* have been introduced, imposing demands on corporate sustainability. However, traditional corporate development models often come at the expense of environmental and social resources, falling short of sustainability requirements. Enterprises urgently need to explore new development pathways and technological approaches to achieve transformation and upgrading [4].

In March 2024, the United Nations General Assembly adopted the global resolution "Seizing the opportunities of safe, secure and trustworthy artificial intelligence systems for sustainable development" for the first time. Against this backdrop, artificial intelligence (AI) technology, which serves as the core driver of the Fourth Industrial Revolution, is affecting corporate production methods, management models, and innovation pathways at an unprecedented rate [5-6]. According to calculations by the China Academy of Information and Communications Technology, the scale of China's AI industry has reached 900 billion yuan, representing a growth rate of 24%. The number of AI enterprises now exceeds 5,300, accounting for approximately 15% of the global total. These data indicate that the deep integration of AI and the real economy has become a significant driving force behind China's economic development. From the micro perspective of enterprises, can the application of AI technology enable the harmonious coexistence of enterprises' economic development and environmental protection? And what are the underlying mechanisms? To address these questions, existing academic research has mainly concentrated on the effect of AI technology application on either enterprises' economic expansion or their environmental contamination. Nevertheless, financial performance and environmental performance are two indispensable components of corporate sustainable development, so focusing on only one of them lacks a holistic perspective. Meanwhile, the failure to reveal the synergistic or restrictive relationship between the two may lead to a dilemma in corporate practice where enterprises focus on one aspect at the expense of the other. Based on this, this study incorporates both corporate financial performance and environmental performance, selects Chinese enterprises as the research objects, and analyzes the relationship between AI application and corporate sustainable development within a more comprehensive framework.

1.2 Literature Review

With the explosive growth of AI technology, literature on its microeconomic consequences has proliferated. Much research focuses on AI's impact on corporate ESG performance, pollution emissions, corporate governance, and social responsibility fulfillment. Leveraging its robust data processing capabilities, precise predictive analytics, and efficient automated execution, AI offers new opportunities and solutions. It can enhance corporate ESG development and coordination performance [7-8]. Conversely, overly advanced AI development may suppress improvements in corporate ESG performance [9]. In environmental management, AI can be applied to reduce corporate pollutant emissions and energy consumption, and enhance resource utilization efficiency

[10]. However, it may also encourage "the ethics of greenwashing", wherein companies superficially adhere to idealistic ethical principles without undertaking substantive or meaningful environmental improvement actions [11]. In corporate governance, AI can enhance the scientific rigor of decision-making. It enables integration across diverse governance domains, such as board performance evaluation, financial distress prediction, and fraud detection, thereby strengthening risk management capabilities and governance standards [12-14]. Regarding social responsibility fulfillment, AI aids in elevating product and service quality while improving employee working conditions. It addresses diverse stakeholder needs and expectations, thereby promoting corporate commitment to and execution of social responsibilities [15-16]. Some scholars contend that increased AI utilization may exacerbate income inequality, undermining social equity and inclusion [17].

Academic research has separately explored the relationship between AI and corporate financial growth, as well as that between AI and corporate environmental performance, resulting in a body of literature with diverse perspectives. According to a study by the IBM Institute for Business Value (IBV), the adoption of AI exerts a positively correlated and beneficial impact on the cost of corporate financial functions and specific productivity indicators in the financial domain [18]. According to Boston Consulting Group research, AI applications could reduce global carbon dioxide emissions by 2.6 to 5.3 billion tons by 2030, generating $1.3 to $2.6 trillion in value for enterprises. However, other studies indicate that information technology is a significant source of environmental pollution. Statistics indicate that the manufacturing, use, and disposal of IT equipment directly contribute to approximately 2% of global greenhouse gas emissions, posing challenges for long-term development [19].

In summary, the academic community still has the following research gaps regarding the micro-level sustainable development effects of AI applications: (1) Scholars have primarily established direct relationships between AI and either financial performance or environmental performance. Few frameworks simultaneously incorporate both performance dimensions. This hinders understanding of how AI differentially influences corporate financial and environmental outcomes and impedes analysis of how to balance these two performances to enhance overall sustainability outcomes. (2) As countries roll out AI support policies, literature evaluating the impact of individual AI policies on corporate sustainability has proliferated. Yet few studies examine how AI applications influence both economic and environmental benefits from a synergistic perspective of AI pilot zone policies and pioneer zone policies, nor do they investigate overall impacts. (3) The mechanism of information acquisition capability in transmitting micro-level AI effects remains understudied. The moderating roles of two critical factors–environmental regulatory pressure and market competitiveness–have also not been verified. Addressing these shortcomings is crucial for advancing both theoretical understanding and practical applications in the fields of AI and corporate sustainability.

1.3 Research Purpose

This study aims to construct a fundamental theoretical framework of "AI Empowerment - Financial and Environmental Performance - Sustainable Development Performance" based on the dual perspectives of financial performance and environmental performance, and conducts an in-depth investigation into the impact mechanisms, mediating pathways, and boundary conditions of AI applications on corporate sustainable development performance. The research elucidates the mediating roles of green technology innovation, total factor productivity, and information acquisition capability, while revealing the moderating effects of corporate heterogeneity and external environments.

At the theoretical level, this study integrates theories such as the Porter Hypothesis, Resource-Based View, and Information Economics to explain the comprehensive mechanisms influencing AI's economic and environmental value. By examining the chained transmission from AI applications to corporate green innovation, efficiency enhancement, and information acquisition integration, it addresses the theoretical gaps in explaining how digital technology enables sustainable development. Furthermore, through the validation of multiple moderating pathways, it enriches theories like eco-efficiency and provides new academic perspectives for understanding the complex interactions within intelligent transformation.

At the practical level, this study provides actionable decision-making references for both governments and enterprises. Its findings can offer empirical support for government departments to design targeted policy packages. Meanwhile, by revealing the specific pathways through which AI influences corporate sustainable performance, this research can guide managers to optimize AI technology investment and digital transformation strategies – integrating AI deeply into green innovation and energy management processes to achieve a win-win situation between economic profitability and environmental responsibility. Furthermore, this study can also guide investors to pay greater attention to enterprises' AI applications and environmental governance, promoting the allocation of capital market funds to sustainable development-related fields.

1.4 Research Innovations

This study utilizes data from Chinese enterprises and prefecture-level cities, integrates city-level AI policies, and matches such policy data with that of A-share listed companies to conduct an empirical test on the micro-level sustainable development effects of AI technology application. The paper's contributions are as follows: First, it introduces multidimensional performance metrics, focusing on AI's comprehensive impact on corporate sustainability, which encompasses two core dimensions: economic performance and environmental performance. It attempts to construct a theoretical framework for AI's influence on corporate sustainability, revealing mechanism pathways through three lenses: green innovation effects, efficiency enhancement effects, and information acquisition effects. It further uncovers moderating pathways via environmental regulation and market competition, expanding the research boundaries of the "theoretical black box" surrounding corporate sustainability performance. Second, unlike existing single-policy studies, this paper innovatively incorporates the synergistic effects of "National New Generation AI Innovation Development Pilot Zones" and "National AI Innovation Application Pioneer Zones" policies as proxy indicators for corporate AI technology adoption. This study demonstrates how AI policy coordination drives improvements in corporate financial and environmental performance, as well as its role in enhancing sustainable development outcomes. Third, it analyzes differentiated effects of AI adoption across heavily polluting industries, high-tech sectors, and enterprises with senior management possessing deep environmental expertise. This provides empirical evidence for governments to formulate industry-specific policies and for companies to develop tailored response strategies.

The remaining structure of this paper is as follows. Section 2 elaborates on relevant theories, reviews existing literature, and proposes research hypotheses. Section 3 introduces research design, including model specification, variable definition, and data description. Section 4 presents empirical results, covering baseline regression, identification tests, and a series of robustness tests. Section 5 discusses further analyses, including mediating effect analysis, heterogeneity analysis, and moderating effect analysis. Section 6 summarizes the study, puts forward policy recommendations, and outlines the limitations as well as directions for future research.

2. Theoretical Analysis and Research Hypotheses

2.1 AI Application and Corporate Sustainable Development Performance

AI application involves deeply integrating AI technology into operational management and business processes to achieve AI-driven transformation across R&D, production, sales, and services. From a financial performance perspective, AI management systems optimize internal processes, reduce manual intervention, and lower administrative expense ratios. AI-assisted analysis enables precise capture of consumer demand, mitigates product inventory risks, expands market share, and drives revenue growth. Enterprises can also optimize marketing channels with AI to reduce promotional costs. This dual approach of "cost reduction and efficiency enhancement" drives financial performance growth [20]. Furthermore, AI constitutes a high-level strategic resource for enterprises, delivering sustainable competitive advantages. Numerous companies have innovatively applied AI in financial and tax practices, achieving preliminary successes. This drives the transformation of traditional, labor-intensive financial and tax services toward a new model of "human-machine collaboration and intelligence-driven operations" [21]. This transformation enables enterprises to reallocate resources from low-value activities to high-value innovation, enhancing return on investment and shareholder value. Regarding environmental performance, AI reduces inefficiencies and pollutant generation by intelligently upgrading equipment and processes during production. This cuts environmental pressure at its source. The integration of AI and big data facilitates real-time analysis and tracking of raw material consumption and industrial waste flows. This facilitates production adjustments, thereby improving resource utilization efficiency and optimizing energy structures [22]. Based on circular economy theory, enterprises can optimize logistics routes and promote recycling and reuse through digital technologies like AI algorithms. This enhances production efficiency, resource integration effectiveness, and corporate environmental governance capabilities [23].

From a sustainable development performance perspective, this performance integrates AI's impact on both financial and environmental outcomes. AI applications should inherently enhance corporate sustainable development performance. Research demonstrates that corporate adoption of AI technology significantly reduces financial and management costs while enhancing operational efficiency and financial performance [24]. AI technology effectively protects ecological environments, boosts social production efficiency, optimizes resource allocation, and provides data support for relevant social decision-making and policy formulation [25]. AI not only serves as a tool for achieving sustainability goals at the application level but also drives sustainability-focused R&D at the front end, effectively addressing unsustainable development issues [26]. Based on the above analysis, this paper proposes the following hypothesis.

H1: The application of AI contributes to enhancing corporate sustainable development performance, as well as improving corporate financial and environmental performance.

2.2 Green Innovation Effects of AI Application

Green innovation aims to achieve efficient resource utilization and reduce environmental pollution through the adoption of environmentally friendly technologies [27]. According to knowledge management theory, the process of corporate green innovation requires integrating knowledge and information across multiple domains, including energy conservation, pollution prevention, waste utilization, and clean production. Leveraging its exceptional data recognition and processing capabilities, AI technology can aggregate, integrate, and share green-related information, providing enterprises with a comprehensive and accurate knowledge foundation for green innovation. On the other hand, AI algorithms can broaden and deepen the scope of external knowledge search for enterprises, helping them acquire heterogeneous knowledge and complementary resources, thereby influencing different dimensions of technology integration [28]. This enables breaking through existing technological structures and domain limitations to develop more innovative green solutions. From the perspective of knowledge absorption capacity, AI technology enhances firms' knowledge absorption capacity. This enables businesses to more effectively identify, assimilate, and apply external green technology knowledge, transforming it into internal innovation capabilities. This provides a solid foundation for green innovation.

Existing research indicates that green innovation activities enhance both financial and environmental performance [29]. AI technology thus mediates between its application and sustainable development outcomes. According to the Porter hypothesis, green technological innovation serves as a strategic corporate response to environmental regulations. It reduces bad environmental impacts throughout the entire production cycle, achieving comprehensive enhancement of environmental performance [30]. From a cost-benefit perspective, clean energy production technologies lower corporate energy costs, while end-of-pipe treatment technologies reduce the risk of pollution penalties, thereby decreasing operational expenses [31]. Simultaneously, green product innovation meets growing demand for environmentally friendly goods, generating market premiums and brand value to enhance financial performance. Integrating these mechanisms, AI application strengthens enterprises' green technological innovation capabilities by enhancing knowledge integration and creation, thereby translating into sustainable development advantages. This paper proposes the following hypothesis.

H2: AI application promotes corporate sustainability through the green innovation effect.

2.3 Efficiency Enhancement Effects of AI Application

Total Factor Productivity (TFP) reflects output growth attributable to technological progress, efficiency improvements, and scale effects after accounting for factor input contributions. It serves as a key indicator for measuring corporate development quality. According to biased technological progress theory, technological advancements are often not neutral but tend to conserve certain factors while enhancing the productivity of others. As a typical example of skill-biased technological progress, AI technology application boosts labor productivity through substitution and productivity effects [32]. On one hand, AI automates and intelligently replaces routine labor, handling repetitive and rule-based tasks. This optimizes assembly line production processes, shortens output cycles, and enhances production efficiency. On the other hand, AI liberates labor from low-value-added tasks, redirecting it toward more creative work. This facilitates a more optimal allocation of capital and labor input. European studies reveal that AI accelerates scientific progress, yielding broader and more enduring TFP gains. Moreover, AI's TFP-enhancing effects are more pronounced in service-intensive economies [33].

Existing research indicates that TFP is a crucial driver of sustainable economic development [34] and a key metric for assessing environmental performance [35]. Thus, TFP serves as an intermediary bridge between AI and corporate sustainability performance. From a resource-based view, scarce, TFP comprehensively reflects a firm's core competitiveness. Productivity-leading firms maintain lower average costs despite larger output scales, enabling them to deliver products and services at lower prices or higher quality. This drives profit growth through expanded market share. According to eco-efficiency theory, the optimization of the ratio between economic value and environmental impact is an important prerequisite for achieving corporate sustainable development. Enhancing TFP—particularly green TFP—positively impacts environmental performance. On one hand, TFP improvement signifies optimized resource input structures, reducing environmental pressure at the source. On the other hand, from a pollution reduction perspective, TFP improvement implies intensified factor utilization through technological progress. This lowers pollution emissions per unit output and reduces environmental burdens in production processes. Synthesizing the above analysis, AI technology application can enhance corporate TFP. Subsequently, it improves sustainability performance through economies of scale and structural efficiency optimization. This paper proposes the following hypothesis.

H3: AI application promotes corporate sustainable development through efficiency enhancement effects.

2.4 Information Acquisition Effects of AI Application

Information acquisition capabilities typically manifest as reduced information asymmetry and enhanced disclosure levels. The former reflects a firm's capacity to gather and integrate internal operational and external market information. The latter indicates transparency and timeliness in communicating information to stakeholders. Based on information asymmetry theory in information economics, uneven information distribution between transaction parties leads to adverse selection and moral hazard [36], generating agency costs and transaction costs. AI's capabilities in big data acquisition, intelligent algorithms, and robust information matching transform corporate information gathering methods. This enhances the comprehensiveness and timeliness of information acquisition [37], thereby addressing information asymmetry. Simultaneously, AI's automated data collection and integration functions reduce external information acquisition costs for enterprises. It also diminishes reliance on specific suppliers, strengthening bargaining power and further lowering transaction costs. According to signaling theory, in markets with information asymmetry, enterprises can proactively disclose information to signal their strengths to the market. Traditional corporate information disclosure suffers from issues such as low comparability and lag, reducing information transmission efficiency. AI technology, leveraging natural language generation (NLG) and real-time information collection and updating systems, achieves standardized, real-time, and visualized information disclosure [38]. This enhances signaling effectiveness, elevating corporate transparency and disclosure standards.

Existing empirical research has preliminarily confirmed a positive correlation between information acquisition capabilities and corporate sustainability performance. Liu and Cao [39] argue that exceptional environmental information acquisition capabilities can facilitate the transition from high-carbon to low-carbon, and further to carbon-neutral operations. According to agency theory, information asymmetry between shareholders and management leads to agency costs, diminishing corporate financial performance. Mitigating internal information asymmetry enables shareholders to monitor management actions more comprehensively and promptly, thereby reducing agency costs. Simultaneously, this addresses management's cognitive limitations, assisting them in making more scientifically sound decisions [40] and improving investment returns. Stakeholder theory posits that sustainable corporate development requires balancing stakeholder relationships and expectations. Information acquisition capabilities meet diverse stakeholder information needs, coordinate interests, and achieve synergistic improvements in both financial and environmental performance. On one hand, high-quality financial disclosures attract long-term investments, alleviating external financing pressures [41] and thereby enhancing corporate market value. On the other hand, enterprises can more promptly identify environmental risks and responsibilities, understand evolving environmental regulatory requirements, and timely disclose compliance status and other green information. This establishes a positive green reputation, earning stakeholder trust and government green subsidy support. This, in turn, improves corporate environmental performance [42]. Synthesizing the above analysis, AI enhances the quality and efficiency of information acquisition through data integration and real-time analysis. Essentially, it mitigates information asymmetry and elevates disclosure quality. The enhancement of information acquisition capability achieves the improvement of sustainable development performance by reducing agency costs and strengthening environmental transparency. Therefore, this paper proposes the following hypothesis.

H4: AI application promotes corporate sustainable development through information acquisition effects.

3. Research Design

3.1 Model Setting

This study employs a multi-period Difference-in-Differences (DID) approach to examine the impact of AI application on corporate sustainable development performance. The benchmark model is set as follows:

$$SDP_{it} = \alpha_0 + \alpha_1 AI_{it} + \alpha_2 Control_{it} + \delta_i + \rho_t + \varepsilon_{it} \quad (1)$$

In Eq. (1), subscripts *i* and *t* denote firm and year, respectively: and SDP_{it} represent firm sustainable performance. AI_{it} indicates the firm's level of artificial intelligence application, measured by the interaction term between the policy shock variable and the implementation time variable ($treat_i \times post_t$). $Control_{it}$ serves as the control variable. δ_i denotes the firm fixed effect. ρ_t represents the year fixed effect, and ε_{it} represents the random disturbance term.

3.2 Variable

3.2.1 Dependent variables

Corporate Sustainable Development Performance (SDP). Corporate sustainable development refers to the adoption of technological approaches that can alleviate environmental pressures or create environmental value, while generating financial value for the enterprise and promoting the growth of the entire economic system [43], thereby achieving the provision of products and services. Consequently, research on AI and corporate sustainability must address both financial performance and environmental effectiveness dimensions [44]. For instance, AI helps businesses detect and analyze credit risks, improving loan creditworthiness to minimize financial risks [45]. It also enhances asset return rates by increasing process automation and reducing operational costs [46]. Magazzino *et al.,* [47] argue that AI-enabled smart grids, smart logistics, and smart production systems optimize energy and material flows while reducing unnecessary resource waste and pollution emissions.

Thus, this study references research by Endrikat [48] and Alexopoulos *et al.,* [49] to measure SDP from two dimensions: financial performance (FP) and environmental performance (EP). FP is measured using the return on total assets (net profit / average total assets). EP is measured using the environmental responsibility score from the Huazheng ESG Rating Agency's mainstream and authoritative scoring system. Both measures are subsequently standardized. Following the methodologies of Zang and Li [50] and Wu *et al.,* [51], the standardized financial performance and environmental performance are synthesized into a composite sustainability performance metric using the following Eq. (2):

$$SDP = \frac{(1-|FP-EP|)\times\sqrt{FP\times EP}}{1} \quad (2)$$

3.2.2 Independent variable

Artificial Intelligence Application (AI). Existing research categorizes the measurement methodologies of AI applications at the enterprise level into three primary approaches. The first employs text mining methods. The proportion of AI-related keywords in the total word frequency within the annual reports of publicly listed companies is selected to measure the application level of AI [52]. The second employs single-indicator approaches. This includes using industrial robot data published by the International Federation of Robotics (IFR) across industries [53] to measure AI adoption levels through enterprise robot penetration rates or utilizing AI patent data as a proxy indicator for AI application [54]. Policies and regulations on the application of AI constitute the third category. Based on the underlying logic of "AI policy – urban intelligent transformation – enterprise AI application" [55], the level of enterprise AI application is assessed by whether the region where the enterprise is located has implemented AI-supporting policies. The selection of AI policies primarily focuses on China's "New Generation of National AI Innovation Development Pilot Zones" and "AI Innovation Application Pioneer Zones," alongside the "US AI Strategy."

This study refers to the third measurement method. China's Ministry of Science and Technology established three batches of pilot cities in 2019, 2020, and 2021. The Ministry of Industry and Information Technology (MIIT) released lists of national AI innovation application pilot zones in 2019, 2021, and 2022. Considering the lag in policy effects, pilot cities approved after September were assigned to the following year. Accordingly, policy shock variables ($\mathrm{treat_i}$) and implementation year variables ($\mathrm{post_t}$) were established. Specifically, enterprises in cities designated as pilot zones or demonstration zones were assigned to the experimental group ($\mathrm{treat_i}$=1), while others formed the control group ($\mathrm{treat_i}$=0). Enterprises in pilot zones for less than two years were treated as control group members. The year of city was coded as 1 for the year of designation and subsequent years ($\mathrm{post_t}$=1), and 0 for other years ($\mathrm{post_t}$=0). The interaction term $\mathrm{treat_i} \times \mathrm{post_t}$ served as a proxy variable for AI application.

3.2.3 Control variables

Drawing on studies by Wang [56] and Sun [57], we controlled for other variables potentially influencing corporate sustainable development performance.

Firm size (Size) typically exerts a positive influence on SDP, as larger enterprises are more likely to generate resource surpluses that help facilitate the development of green technology and ESG practices. The impact of firm age (Age) often manifests as a positive or nonlinear relationship. Mature enterprises frequently possess more standardized sustainable management systems and compliance experience, which generally benefits sustainable development. However, organizational rigidity may also produce negative effects on environmental performance. Whether a company is loss-making (Loss) shows a negative correlation with sustainability performance. Loss-making companies often face financial difficulties due to resource constraints and survival pressures, leading them to cut environmental investments to maintain operations. The debt-to-asset ratio (Lev) predominantly exerts a negative influence. Highly leveraged firms face heightened financial risks, potentially reducing capital allocation to sustainability initiatives. The impact of Cash Flow (Cash) is ambiguous. While robust operating cash flow provides funding for green investments and social responsibility, excessive cash reserves may exacerbate agency problems, incentivize managerial myopia, and foster innovation inertia, ultimately harming sustainability performance. The impact of revenue growth rate (Growth) is ambiguous. High-growth companies may neglect environmental investments while focusing on short-term expansion, negatively affecting environmental performance. Conversely, growth may accumulate resources that bolster sustainable development. Management shareholding (Mshare) typically exhibits a positive correlation. Moderate ownership alleviates agency problems by aligning management with long-term sustainable value. Excessively low holdings may create negative impacts due to divergent interests, while excessively high holdings may foster risk aversion. Overall, positive effects prevail within a moderate range. The impact of the largest shareholder's stake (Top) is dual-edged. Moderate equity concentration facilitates the implementation of long-term sustainable strategies, while excessive concentration may lead to interest encroachment or strategic conservatism. Literature more commonly observes positive correlations associated with moderate concentration. The proportion of fixed assets (Fixed) often exhibits a negative influence. Companies with higher ratios face greater equipment retrofitting costs and pollution control expenses, coupled with reduced asset turnover flexibility, which may constrain the pace of sustainable transformation and performance improvement.

3.2.4 Mediating variables

Green Technology Innovation (GTI). Due to time lags in patent authorization, firms often deploy new technologies and products into commercial applications and generate operational returns after filing patent applications. Therefore, this study adopts the methodology proposed by Jin and Zhang [58], using the number of green patents applied for in a given year to measure a firm's green technology innovation. A higher value indicates stronger green innovation capabilities.

Total Factor Productivity (TFP). Current TFP measurement methods primarily fall into three categories: parametric, non-parametric, and semi-parametric. From a methodological perspective, semi-parametric estimation integrates the core concepts of production function estimation and non-parametric estimation, demonstrating superior performance in addressing the jointness bias and selection bias issues encountered in TFP measurement. This study employs the LP method① to calculate firm TFP [59-60]. Higher value indicates greater efficiency.

Information Access Capability (IAC). External access to corporate information typically depends on the degree of asymmetry and the quality of information disclosure. This study employs the ASY index and KV index for measurement [61]. Specifically, the ASY index utilizes principal component scores from three indicators: liquidity ratio, illiquidity ratio, and yield reversal. A higher ASY value indicates greater information asymmetry. The KV index is measured by the coefficient of trading volume's impact on investor stock returns, where a higher KV value indicates lower information disclosure quality. Subsequently, this study calculates the ASY and KV indices using the entropy method. This yields a composite indicator (IAC) representing the difficulty of information acquisition for firms. For the convenience of discussion, the calculation results are treated as negative values. A higher IAC value indicates lower information acquisition difficulty.

3.2.5 Moderating variables

Environmental Regulation Strength (ERS). A comprehensive framework for measuring environmental regulation has been established. Common approaches focus on government management dimensions, including the number and enforcement intensity of environmental policies, the frequency of government oversight and inspections of corporate pollution activities, and the amount of pollution fees② levied on enterprises. Drawing on the research of Levinson [62] and Li *et al.,* [63], this study employs actual enterprise pollution discharge fees paid as a proxy indicator for environmental regulatory intensity. A higher value indicates greater environmental regulatory intensity faced by enterprises.

Market Competition Intensity (MCI). Drawing on the research of Kale and Loon [64], this study introduces the Lerner Index, as shown in Eq. (3). This index reflects an enterprise's pricing power within its industry. A higher value indicates greater monopolistic power and lower market competition intensity. For analytical convenience, the Lerner Index is negatively scaled to serve as a proxy for market competitiveness.

$$Lerner\ Index = \frac{Revenue - Cost\ of\ Sales - Selling\ Expenses - Administrative\ Expenses}{Revenue} \quad (3)$$

Specific definitions and measurements of each variable are shown in Table 1.

Table 1
Variable definitions

Variable Name	Variable Symbol	Calculation Method
Corporate Sustainable Development Performance	SDP	Standardization of Environmental Scores in the Huazheng ESG Rating System
Corporate Financial Performance	FP	Standardized Return on Total Assets
Corporate Environmental Performance	EP	Standardized Financial Performance and Environmental Performance Calculations Yield
Artificial Intelligence Application	AI	$\times post_t treat_i$
Firm Size	Size	ln(Total Company Assets)
Firm Age	Age	ln(Current Year - Year of Establishment + 1)
Loss Status	Loss	If current year's net profit is less than 0, set to 1; otherwise set to 0
Debt-to-Asset Ratio	Lev	Total Liabilities / Total Assets
Cash Flow Ratio	Cash	Net Cash Flow from Operating Activities / Total Assets
Revenue Growth Rate	Growth	ln(1 + (Current Revenue Change / Previous Year's Revenue))
Management Shareholding Ratio	Mshare	Management Shareholding Count / Total Shares
Largest Shareholder Ownership Ratio	Top	Largest Shareholder's Holdings/Total Shares
Fixed Assets Ratio	Fixed	Net Fixed Assets / Total Assets
Green Technology Innovation	GTI	ln(1+Green Patent Applications)
Total Factor Productivity	TFP	TFP calculated using the LP method
Information Access Capability	IAC	Calculated using ASY and KV indices
Environmental Regulation Strength	ERS	Standardized Actual Pollution Discharge Fees (Environmental Tax) Paid by Enterprises
Market Competition Intensity	MCI	- Lerner Index

3.3 Data Sources

This study examines all A-share listed companies in China from 2013 to 2023. To ensure research accuracy, the original sample underwent the following processing: First, companies with abnormal trading status (ST, *ST, PT) were excluded. Next, firms with excessive missing values were removed, with individual missing data points filled using interpolation methods. Finally, firm data was matched with pilot city data to generate balanced panel data comprising 1,925 firms, 297 cities, and 21,175 observations. Green patent data for listed companies was sourced from the CNIPA. Other microdata was obtained from the CSMAR database, CNRDS database, Wind database, and annual reports of listed companies.

Descriptive statistics and multicollinearity test results for key variables are presented in Table 2. It indicates that the standard deviation of SDP is 0.0440, suggesting minimal variation in SDP across firms. With a minimum value of 0 and a mean (0.3827) close to the median (0.3932), the data distribution is relatively balanced but exhibits slight left skewness. The Independent variable (AI), a dummy variable, has a mean of 0.1272 and standard deviation of 0.3332, indicating the experimental group has a smaller sample size than the control group. Although the smaller experimental group sample might lead to non-significant results, it still meets statistical requirements. Moreover, the significant economic effect does not undermine the core conclusion that policies promote improvements in corporate sustainable development performance. Furthermore, the VIF values for all variables indicate no severe multicollinearity issues.

Table 2
Descriptive statistics of variables

Variables	Obs	Mean	Std. Dev	Min	Max	VIF
SDP	21175	0.3827	0.0440	0	0.6281	
FP	21175	0.4030	0.0313	0	1	
EP	21175	0.4784	0.1207	0	1	
AI	21175	0.1272	0.3332	0	1	1.11
Size	21175	22.7484	1.5356	18.3419	31.4309	2.28
Age	21175	3.0211	0.3156	0.0077	4.0510	1.20
Loss	21175	0.1142	0.3181	0	1	1.63
Lev	21175	0.4480	0.2036	-0.1107	1.5923	1.78
Cash	21175	0.0485	0.0701	-0.7443	0.8759	1.31
Growth	21175	0.0930	0.3449	-7.0633	7.5387	1.12
Mshare	21175	0.0874	0.1549	0	1.0565	1.26
Top	21175	0.3312	0.1503	0.0029	0.8999	1.13
Fixed	21175	0.2081	0.1645	0	0.9542	1.14
GTI	21175	0.2993	0.7581	0	6.9266	1.06
TFP	21175	9.5747	1.7011	0	16.1810	1.63
IAC	21175	-0.3693	0.1175	-0.7240	-0.1001	1.12
ERS	21175	0.0072	0.0275	0	1	1.19
MCI	21175	-0.1350	0.2053	-1	4.7810	1.93

4. Results

4.1 Benchmark Regression Results

The benchmark regression results are presented in Table 3. Columns (1) to (2) examine corporate sustainability performance. Columns (3) to (6) examine financial performance and environmental performance, respectively. Based on the regression results from the two-way fixed effects model, regardless of whether control variables are included, the coefficient of AI application on corporate SDP, FP, and EP is significantly positive at the 1% level. This indicates that corporate AI applications significantly enhance sustainability performance, including financial performance and environmental-social performance, thereby validating H1.

Table 3
Benchmark regression results

Variables	(1) SDP	(2) SDP	(3) FP	(4) FP	(5) EP	(6) EP
AI	0.0052*** (0.0016)	0.0063*** (0.0015)	0.0052*** (0.0011)	0.0070*** (0.0008)	0.0190*** (0.0047)	0.0186*** (0.0047)
Size		0.0039*** (0.0011)		0.0049*** (0.0007)		0.0209*** (0.0030)
Age		0.0162** (0.0076)		0.0058 (0.0038)		-0.0047 (0.0196)
Loss		-0.0335*** (0.0012)		-0.0432*** (0.0010)		0.0017 (0.0026)
Lev		-0.0353*** (0.0041)		-0.0532*** (0.0030)		-0.0277*** (0.0103)
Cash		0.0366*** (0.0057)		0.0725*** (0.0078)		0.0248** (0.0112)
Growth		0.0054*** (0.0011)		0.0112*** (0.0011)		-0.0105*** (0.0021)

Table 3
Continued

Variables	(1) SDP	(2) SDP	(3) FP	(4) FP	(5) EP	(6) EP
Mshare		0.0143*** (0.0054)		0.0134*** (0.0041)		0.0512*** (0.0143)
Top		0.0110* (0.0064)		0.0054 (0.0037)		0.0028 (0.0170)
Fixed		-0.0113** (0.0056)		-0.0299*** (0.0034)		0.0244* (0.0135)
Cons	0.3820*** (0.0002)	0.2582*** (0.0345)	0.4024*** (0.0001)	0.3011*** (0.0192)	0.4760*** (0.0006)	0.0160 (0.0875)
Fixed enterprise	Yes	Yes	Yes	Yes	Yes	Yes
Fixed year	Yes	Yes	Yes	Yes	Yes	Yes
N	21175	21175	21175	21175	21175	21175
R^2	0.407	0.477	0.384	0.653	0.556	0.561

Note: *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are shown in parentheses. The same applies below.

4.2 Identifiability Test

4.2.1 Parallel trend test

This study employs an event study approach [65], with the research period spanning 6 years before and 4 years after policy implementation. As shown below:

$$SDP_{it} = \beta_0 + \sum_{k=-4}^{6} \beta_k (treat_i \times post_t^k) + \beta_j Control_{it} + \delta_i + \rho_t + \varepsilon_{it} \quad (4)$$

Figure 1 indicates that prior to the implementation of the AI policy, the coefficient β_k is insignificant and different from zero, demonstrating the model passes the test. Similarly, parallel trend tests were also passed when the dependent variables were financial performance and environmental performance.

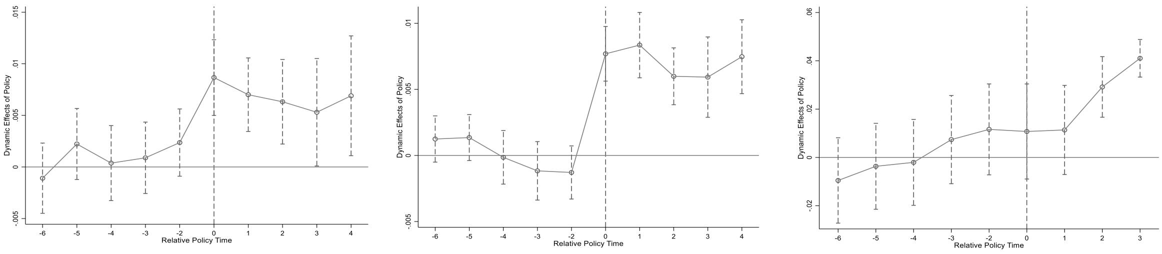

Fig. 1. Parallel trend test
Note: From left to right, the figures represent sustainable development performance (SDP), financial performance (FP), and environmental performance (EP)

4.2.2 Placebo test

To further test the robustness of the DID model and ensure the rigor of the research findings, firms were randomly selected from all samples to form the experimental group. Different policy time points were then assigned to this fictitious experimental group. Regression results were obtained by repeating the DID regression 500 times. Figure 2 shows that all passed the placebo test.

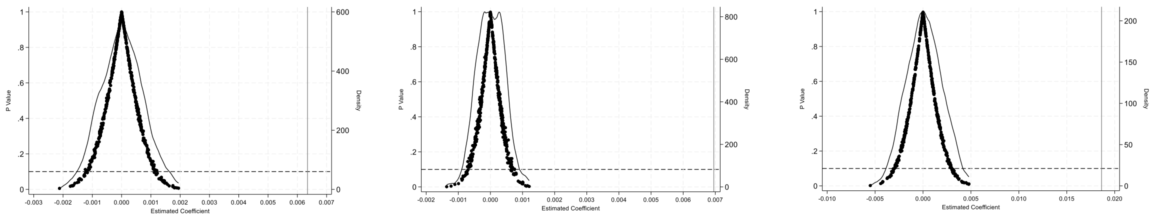

Fig. 2. Placebo test result
Note: From left to right, the figures represent sustainable development performance (SDP), financial performance (FP), and environmental performance (EP)

4.3 Robustness Tests
4.3.1 Endogeneity test

(1) PSM-DID. Sample self-selection bias may introduce endogeneity issues. This study employs PSM-DID to test the model. Specifically, the propensity score is estimated using Logit regression [66]. Subsequently, the experimental and control groups are matched using the nearest neighbor matching method, and the re-estimated model is based on the matched samples, as shown in columns (1) to (3) of Table 4. The coefficients for AI are statistically significant at the 1% level for both SDP and FP, EP. The benchmark regression results remain robust.

(2) Instrumental Variable Method. Terrain ruggedness may influence local AI technology adoption. However, as terrain ruggedness is formed by geological history and does not directly affect a firm's current sustainable development performance, it satisfies the conditions of exogeneity and relevance and is thus suitable to be used as an Instrumental variable [67-68]. Subsequently, the number of AI patent applications filed by the firm was introduced to capture the time-varying nature of the instrumental variable. An interaction term between terrain ruggedness and the firm's AI patent applications from the previous year was constructed as the final instrumental variable. Estimation was conducted using two-stage least squares (2SLS), with results presented in columns (4) to (6) of Table 4. The instrumental variable coefficients in the first stage were all significantly negative (table omitted), indicating a significant negative relationship between topographic variation and AI. The LM statistics were significant at the 1% level, and the F statistics exceeded the 10% critical value (16.38). Thus, we reject the null hypotheses of "insufficient instrument identification" and "weak instruments," confirming the validity of the instrumental variables selection. Simultaneously, the regression coefficients for AI in the second stage are all positive and pass the significance test (except for the coefficient on FP, which is negative but fails the significance test). These results indicate that after mitigating endogeneity issues, the application of AI still significantly enhances corporate sustainable development performance.

4.3.2 Other robustness tests

(1) Heterogeneity-of-Treatment Effects Test. To address potential heterogeneous treatment effects bias in multi-period DID estimation arising from negative weights, this study first employs Goodman-Bacon's [69] decomposition technique. The two-way fixed effects model is decomposed into multiple 2×2-DID estimators, with treatment effects and weights calculated separately for each. As shown in columns (1) to (4) of Table 5 and the decomposition results in Figure 3, regardless of whether the dependent variable is SDP, FP, or EP, the group weights with the "never-treated group" as the control group reach as high as 91.3%. This study also employs a counterfactual method based on interpolation, proposed by Borusyak *et al.,* [70], for heterogeneity-robust estimation (denoted as AI_Borusyak). As shown in columns (5) to (7) of Table 5, the estimated coefficients for AI_Borusyak

are all significantly positive. Thus, even after accounting for treatment heterogeneity, the conclusions drawn earlier.

Table 4
Endogeneity test results

	PSM-DID			Instrumental Variable Method		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	SDP	FP	EP	SDP	FP	EP
AI	0.0077***	0.0071***	0.0143***	0.1048**	-0.0087	0.2922**
	(0.0016)	(0.0009)	(0.0048)	(0.0415)	(0.0155)	(0.1258)
K-P rk LM statistic				20.609***	20.609***	20.609***
K-P rk Wald rk F statistic				22.099	22.099	22.099
Cons	0.2557***	0.2929***	0.0741	0.3502***	0.3486***	0.0393
	(0.0387)	(0.0234)	(0.0935)	(0.0205)	(0.0085)	(0.0621)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Fixed enterprise	Yes	Yes	Yes	Yes	Yes	Yes
Fixed year	Yes	Yes	Yes	Yes	Yes	Yes
N	16492	16492	16492	21175	21175	21175
R^2	0.426	0.616	0.568	0.983	0.997	0.919

Table 5
Results of the heterogeneity-robust estimates

Variables	Bacon Test Estimated Coefficient			Bacon Test Weight	Borusyak Test		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	SDP	FP	EP	Weight	SDP	FP	EP
AI_Borusyak					0.0063***	0.0069***	0.0212***
					(0.0016)	(0.0008)	(0.0048)
Earlier T vs. Later C	0.009	0.013	-0.015	0.058			
Later T vs. Earlier C	0.008	0.011	-0.027	0.028			
T vs. Never treated	0.005	0.004	0.022	0.913			

Note: T = Treatment; C = Comparison.

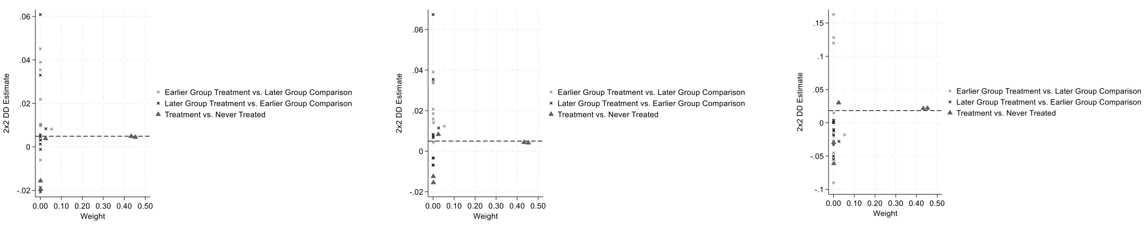

Fig. 3. Bacon decomposition diagram
Note: From left to right, the figures represent sustainable development performance (SDP), financial performance (FP), and environmental performance (EP)

(2) Double Machine Learning. When setting up regression models, estimation biases may arise due to the "curse of dimensionality" and multicollinearity issues. Therefore, this study adopts a double machine learning approach, referencing Bodory and Huber [71], and the sample split ratio is set at 1:4. To avoid subjective model selection bias, a general interactive double machine learning model was employed, utilizing the Random Forest prediction algorithm. Lasso regression was

additionally applied for auxiliary validation. As shown in Table 6, AI's regression coefficient remains positive, confirming the robustness.

Table 6
Results of double machine learning

Variables	Random Forest			Lasso Regression		
	(1)	(2)	(3)	(4)	(5)	(6)
	SDP	FP	EP	SDP	FP	EP
AI	0.0074***	0.0075***	0.0167***	0.0114***	0.0062***	0.0253***
	(0.0008)	(0.0005)	(0.0025)	(0.0009)	(0.0005)	(0.0024)
Cons	0.0011***	-0.0001	-0.0011	0.0000	-0.0000	-0.0000
	(0.0002)	(0.0001)	(0.0007)	(0.0003)	(0.0002)	(0.0008)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Fixed enterprise	Yes	Yes	Yes	Yes	Yes	Yes
Fixed year	Yes	Yes	Yes	Yes	Yes	Yes
N	21175	21175	21175	21175	21175	21175

(3) Replacing the Dependent Variable. Following the methodology of Zhang and Yu [72], this study employs Tobin's Q ratio to measure financial performance (denoted as FP2) and Bloomberg ESG Ratings environmental scores to measure environmental performance (denoted as EP2). The corporate sustainability performance (denoted as SDP2) was recalculated using Eq. (2) and subjected to regression analysis. Neither the significance nor the correlation of the AI coefficient changed, as shown in columns (1) to (3) of Table 7.

(4) Excluding Policy Interference. Other policies during the sample period may confound conclusions. This study focuses on policies such as "Smart Manufacturing Pilot Demonstration," "National Big Data Comprehensive Pilot Zones," and "Green Finance Reform and Innovation Pilot Zones." These policies may influence corporate sustainability performance, potentially obscuring the impact of AI policies [73]. Therefore, this study constructs dummy variables for the three policies (denoted as Policy_1, Policy_2, Policy_3) and incorporates them into the baseline regression model for control. The results are shown in columns (4) to (7) of Table 7. After controlling interfering policies, the positive correlation between AI and SDP, FP, and EP remains significant.

(5) Eliminating Urban Samples. Municipalities directly under central government and provincial capitals possess regional advantages in politics, economy, culture, and technology compared with other cities. Enterprises located in these areas exhibit distinct characteristics relative to others, potentially introducing interference into model results. After excluding the interfering factors of these cities, the impact coefficients of AI on SDP, FP, and EP remain significantly positive, as shown in columns (7) to (9) of Table 7.

5. Further Discussion

5.1 Testing the Mechanism of Action

The theoretical section above has elucidated the mechanism through which AI applications influence corporate sustainable development performance from three perspectives: green innovation effects, efficiency enhancement effects, and information acquisition effects. However, the extent of these impacts requires further validation. This paper adopts two-step approach [74]. Using green technological innovation, total factor productivity, and information acquisition capability as mediating variables, we construct the mechanism testing model as shown in Eq. (5). Where, M_{it} denotes the mediating variable.

$$M_{it} = \alpha_0 + \alpha_1 AI_{it} + \alpha_2 Control_{it} + \delta_i + \rho_t + \varepsilon_{it} \tag{5}$$

Table 7
Robustness test results

Variables	Replacing the Dependent Variable			Excluding Policy Interference			Eliminating Urban Samples		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	SDP2	FP2	EP2	SDP	FP	EP	SDP	FP	EP
AI	0.0159***	0.0031***	0.0127***	0.0058***	0.0077***	0.0148***	0.0078***	0.0074***	0.0209***
	(0.0010)	(0.0012)	(0.0049)	(0.0016)	(0.0008)	(0.0049)	(0.0017)	(0.0009)	(0.0049)
Policy_1				-0.0034	-0.0011	0.0214**			
				(0.0032)	(0.0015)	(0.0103)			
Policy_2				0.0015	-0.0026***	0.0140***			
				(0.0015)	(0.0008)	(0.0036)			
Policy_3				0.0007	0.0009	0.0010			
				(0.0040)	(0.0020)	(0.0095)			
Cons	0.2119***	0.4356***	-0.0894	0.2587***	0.3005***	0.0196	0.2625***	0.3005***	0.0537
	(0.0269)	(0.0439)	(0.1179)	(0.0346)	(0.0191)	(0.0872)	(0.0367)	(0.0198)	(0.0940)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed enterprise	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	21175	21175	21175	21175	21175	21175	19113	19113	19113
R^2	0.532	0.606	0.678	0.477	0.653	0.562	0.483	0.653	0.562

5.1.1 Green innovation effect

As shown in columns (1) and (2) of Table 8, the coefficient of AI is positive at the 10% level. It indicates that AI application enhances firms' capacity to analyze large-scale data. Consequently, firms can more readily identify potential green technology innovation opportunities and precisely target R&D directions for green technologies, thereby improving green innovation efficiency. Current studies regarding the connection between green technological innovation and corporate sustainability performance demonstrate the following: On one hand, green technological innovation helps enterprises reduce energy consumption and pollutant emissions through end-of-pipe treatment and process improvements. On the other hand, it enhances market competitiveness by designing green products and packaging. This creates market opportunities for enterprise development. Consequently, enterprises can fulfill environmental responsibilities while opening more profit growth channels, achieving a win-win outcome of economic and environmental benefits. Therefore, it is conducive to the long-term sustainable development of enterprises [75]. H2 is validated.

5.1.2 Efficiency enhancement effect

As shown in columns (3) and (4) of Table 8, the coefficient for AI remains consistently positive. It indicates that introducing AI technology enhances firms' control and oversight across production stages. This facilitates semi-automation or even full automation of production lines, thereby reducing labor costs and lowering defective product rates. It helps firms further improve overall production efficiency [76]. Existing research indicates that TFP plays a crucial role in sustainable development [77]. An increase in TFP means enterprises can achieve greater output with fewer inputs. This directly lowers production costs per unit and improves economic efficiency. Simultaneously, it provides a solid financial foundation for sustainable development. Enterprises can allocate more funds to R&D, environmental protection, social responsibility, and other areas, driving long-term stable growth. H3 is thus validated.

5.1.3 Information access effect

As shown in columns (5) and (6) of Table 8, the coefficients for AI are positive and pass the significance test. The application of artificial intelligence technology enhances the convenience of information acquisition for enterprises. By collecting real-time, multi-source information across domains and entities, AI broadens enterprises' information channels. This mitigates information asymmetry between enterprises and markets, as well as between enterprises and external investors. Simultaneously, AI technologies utilize automated algorithms to verify data and establish unified standards, enhancing the transparency and comparability of information disclosure [78]. Existing research indicates that improved information access optimizes management investment decisions and enhances corporate capital allocation efficiency. Furthermore, high-quality disclosure increases financial institutions' willingness to supply funds to enterprises. This boosts financing accessibility, enabling companies to secure lower capital costs for environmental investments. Ultimately, it effectively promotes improvements in corporate sustainability performance [79]. H4 is thus validated.

Table 8
Test results of mechanism

Variables	Green Innovation Effect		Efficiency Enhancement Effect		Information Acquisition Effect	
	(1) GTI	(2) GTI	(3) TFP	(4) TFP	(5) IAC	(6) IAC
AI	0.0432*	0.0416*	0.0295	0.0363*	0.0093**	0.0109***
	(0.0236)	(0.0236)	(0.0244)	(0.0205)	(0.0040)	(0.0039)
Cons	0.2938***	-1.1963**	9.5710***	-0.1990	-0.3705***	-0.2949***
	(0.0030)	(0.5725)	(0.0031)	(0.5331)	(0.0005)	(0.0837)
Control Variables	No	Yes	No	Yes	No	Yes
Fixed enterprise	Yes	Yes	Yes	Yes	Yes	Yes
Fixed year	Yes	Yes	Yes	Yes	Yes	Yes
N	21175	21175	21175	21175	21175	21175
R^2	0.631	0.632	0.928	0.947	0.269	0.290

5.2 Heterogeneity Analysis

5.2.1 Corporate pollution levels

Companies with differing pollution levels exhibit significant variations in government scrutiny, strategic objectives, and management practices. Therefore, this study references industry classification guidelines for listed companies issued by the China Securities Regulatory Commission and environmental protection authorities③. Companies are categorized into heavy pollution and non-heavy pollution. As shown in Figure 4, AI adoption exhibits a more pronounced positive impact on the sustainable development performance and financial performance of non-heavy pollution enterprises, while its effect on heavy pollution enterprises is insignificant or minimal. Conversely, AI adoption demonstrates a greater capacity to enhance environmental performance in heavy pollution enterprises. It is because sustainable development performance integrates financial and environmental outcomes, an area where non-heavy pollution enterprises hold an overall advantage. This stems primarily from their robust financial performance foundation and lower environmental compliance pressures. Introducing AI technology enhances the flexibility and low environmental impact characteristics of existing business models, asset structures, and management systems, thereby boosting overall performance. In contrast, heavy pollution enterprises face high-energy-consumption assets and entrenched production models, making AI transformation difficult and time-consuming. Furthermore, for non-heavy pollution enterprises, AI applications directly serve core business operations and customers. Financial returns are rapid and substantial, while environmental benefits often emerge as secondary dividends. For heavy pollution enterprises, the primary goal of AI adoption is often reactive compliance management and risk avoidance. Economic returns are indirect and lagging, resulting in less tangible financial contributions. This dampens overall performance [80]. Notably, AI demonstrates more pronounced environmental performance improvements for heavy pollution enterprises, further validating the preceding analysis.

5.2.2 Enterprise technological capability

Enterprises with differing technological levels exhibit variations in resource accumulation, innovation capacity, and government support. Therefore, high-tech industries in this study are defined based on the "Measures for the Administration of High-Tech Enterprise Certification" issued in 2008 and the major categories outlined in the revised "Guidelines for the Classification of Listed Companies by Industry" from 2012④. Based on this classification, enterprises are grouped into high-tech enterprises and non-high-tech enterprises. As shown in Figure 4, AI adoption exerts a more pronounced positive impact on the sustainable development performance and financial performance of high-tech enterprises, while its effect on non-high-tech enterprises is insignificant or minimal. Furthermore, AI adoption demonstrates a greater capacity to enhance environmental performance in non-high-tech enterprises. Maybe because high-tech enterprises' core competitiveness lies in "technological R&D and innovation capabilities," making their technological systems highly compatible with AI. AI applications can be directly embedded into the core segments of high-tech enterprises' value chains. They optimize product performance, enhance service efficiency, and create new business models, thereby directly driving financial performance growth. Simultaneously, the technology-intensive nature of high-tech enterprises helps lower barriers to green transformation, contributing to improvements in their overall sustainable development performance. In contrast, non-high-tech enterprises often lack sufficient digital infrastructure. The substantial upfront investment in AI applications results in slower short-term returns, limiting overall performance gains. Furthermore, these findings reveal a phenomenon: AI adoption itself generates new environmental costs [81]. While high-tech firms benefit from AI adoption, they often also serve as builders and operators of AI infrastructure. Thus, while they assist other industries in reducing emissions through AI, the hidden energy consumption and emissions from operating their own data centers may partially offset these gains. Conversely, non-high-tech firms primarily function as users of AI technology, avoiding direct responsibility for the environmental costs associated with operating AI infrastructure. Consequently, their environmental performance improvements are more pronounced.

5.2.3 Environmental background of corporate executives

Differences in environmental backgrounds among corporate executives determine their awareness of environmental issues. Such environmental experience becomes internalized in corporate strategic decision-making. Executive environmental background is identified based on the presence of environmental keywords⑤ in their personal resumes [82]. The number of executives with environmental backgrounds is then quantified. Companies with the number of executives with environmental background exceeding the annual average are classified as the group with high environmental background of the top management team (TMT), while those below the average are the low group. Figure 4 demonstrates that AI application exerts a more positive impact on the sustainable development performance and environmental performance of firms with high TMT environmental backgrounds, while yielding greater financial performance enhancement for firms with low TMT environmental backgrounds. This occurs because TMT with environmental experience prioritize corporate green sustainability and exhibit heightened sensitivity and responsiveness to shifts in local fiscal sustainability. Such firms' strategic decisions increasingly favor maximizing long-term sustainable value [83]. Companies prioritize AI deployment in environmental risk management and green value creation, simultaneously enhancing environmental performance while reducing the financial pressure from environmental costs. This elevates overall sustainable development performance. In contrast, companies with executives lacking environmental backgrounds primarily focus their strategies on maximizing short-term financial profits. AI deployment is concentrated in activities directly generating sales revenue and profit growth. This approach yields short-term gains in cost reduction, efficiency improvements, and enhanced financial performance. However, neglecting environmental performance support limits overall sustainable development outcomes.

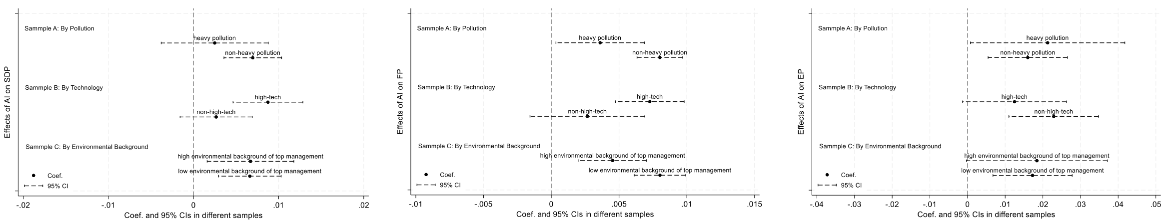

Fig. 4. Heterogeneity test results
Note: From left to right, the figures represent sustainable development performance (SDP), financial performance (FP), and environmental performance (EP)

5.3 Moderating Effect Analysis

The following moderating model is developed in this study. In Eq. (6), $\mathrm{W_{it}}$ represents the moderator variable, while $\mathrm{AI_{it}} \times \mathrm{W_{it}}$ denotes the interaction term between the explanatory variable and the moderating variable.

$$SDP_{it} = \alpha_0 + \alpha_1 AI_{it} + \alpha_2 W_{it} + \alpha_3 AI_{it} \times W_{it} + \alpha_4 Control_{it} + \delta_i + \rho_t + \varepsilon_{it} \tag{6}$$

5.3.1 Moderating role of environmental regulatory intensity

Environmental regulatory intensity is a key institutional factor governing corporate public environmental behavior. Existing research indicates that when facing stringent regulatory measures, enterprises may proactively reflect on their developmental shortcomings and actively advance ESG initiatives. They may further leverage AI technology to achieve integrated and coordinated development [84]. Alternatively, such regulations may increase operational burdens, diverting resources originally allocated for ESG development. This could weaken the performance-enhancing effects of AI [85].

The moderation model results for ERS are presented in Columns (1) to (3) of Table 9. The ERS × AI interaction coefficient is significantly negative when the dependent variable is SDP or FP, and significantly positive when the dependent variable is EP. Environmental regulatory strength exerts a negative moderating effect on AI's promotion of corporate sustainable development performance and financial performance enhancement. Conversely, it exerts a positive moderating effect on AI's promotion of corporate environmental performance improvement. The rationale is as follows: increased environmental regulatory intensity creates broader market demand and policy support for AI applications in environmental protection. This incentivizes enterprises to actively explore and adopt AI, amplifying its positive impact on environmental performance. However, excessive regulation also elevates compliance costs and diverts resources. Even though AI can optimize production processes and yield cost savings, these benefits may not materialize in the short term. Consequently, the financial performance gains from AI implementation are diminished.

5.3.2 Modulating role of market competitiveness

Market competitiveness reflects the intensity of the external market environment faced by enterprises and indicates their own competitive position in the market. Existing research indicates that intense market competition may stimulate corporate drive. Companies may leverage AI to enhance core competitive advantages and achieve sustainable development [86]. Conversely, it may suppress corporate vitality, exacerbate market information asymmetry and monopoly risks [87], thereby weakening AI's performance-enhancing effects.

The moderation model results for Market Competition Intensity (MCI) are presented in columns (4) to (5) of Table 9. The MCI×AI interaction coefficient is significantly positive when the dependent variable is SDP or FP, but significantly negative when the dependent variable is EP. Market competitiveness intensity exerts a positive moderating effect on AI's promotion of sustainable development performance and financial performance enhancement. However, it exerts a negative moderating effect on AI's promotion of environmental performance enhancement. The reason may be as follows: In highly competitive markets, survival pressures compel enterprises to apply AI technology in areas that directly generate benefits, such as automated production and precision marketing. This amplifies the financial returns of AI. On the other hand, accelerated competition drives rapid changes in market demand. Simple efficiency improvements may be quickly imitated by competitors. To capture excess profits, enterprises leverage AI for product and business model innovation to achieve differentiation This fosters sustainable competitive advantages. Yet the same competitive pressures suppress corporate motivation to leverage AI for environmental performance enhancement. This is because improving environmental performance constitutes a positive external activity, which is benefiting society more broadly. Firms in competitive markets must prioritize safeguarding internal profits to maintain external market share, consequently curtailing AI investment in environmental dimensions. This limits AI's potential to elevate environmental performance [88].

6. Conclusions

6.1 Research Findings

This study examines the impact of AI adoption on corporate sustainability performance by analyzing all listed companies in China from 2013 to 2023 using a multi-period DID model. AI application significantly enhances corporate financial and environmental performance, substantially improving overall sustainability outcomes. These findings remain robust after endogeneity tests and a series of sensitivity analyses. AI technology application promotes green technological innovation, enhances total factor productivity, and strengthens information acquisition capabilities, thereby positively influencing corporate sustainability performance. Heterogeneity analysis reveals that the positive effect of AI on sustainability is more pronounced when firms in non-heavy pollution or high-tech industries, and when their executives possess deeper environmental expertise. Further, the more rigorous environmental regulatory policies are, the feebler the promotional function AI has on enterprises' sustainable development performance. The higher the market competitiveness, the stronger the driving effect of AI on corporate sustainable development performance.

Table 9
Moderating effects

Variables	Environmental Regulation Strength			Market Competition Intensity		
	(1)	(2)	(3)	(4)	(5)	(6)
	SDP	FP	EP	SDP	FP	EP
AI	0.0067***	0.0069***	0.0171***	0.0067***	0.0073***	0.0182***
	(0.0015)	(0.0008)	(0.0047)	(0.0015)	(0.0008)	(0.0047)
ERS	-0.0154	0.0642**	0.3019*			
	(0.0350)	(0.0252)	(0.1821)			
ERS×AI	-0.0642**	-0.0186*	0.2045***			
	(0.0281)	(0.0101)	(0.0613)			
MCI				-0.0260***	-0.0402***	0.0059
				(0.0053)	(0.0069)	(0.0082)
MCI×AI				0.0196***	0.0158**	-0.0396***
				(0.0051)	(0.0065)	(0.0101)
Cons	0.2533***	0.3051***	0.0513	0.2745***	0.3280***	0.0163
	(0.0348)	(0.0194)	(0.0871)	(0.0345)	(0.0194)	(0.0878)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Fixed enterprise	Yes	Yes	Yes	Yes	Yes	Yes
Fixed year	Yes	Yes	Yes	Yes	Yes	Yes
N	21175	21175	21175	21175	21175	21175
R^2	0.424	0.618	0.518	0.428	0.638	0.517

6.2 Policy Implications

First, systematically refine the AI policy framework and optimize both the soft and hard environments for AI development. Governments should strengthen top-level design by establishing a multi-tiered AI governance structure involving governments, industry organizations, enterprises, and the public. Promote the widespread implementation of "AI+" initiatives. Regarding the soft environment, actively promote the orderly opening and cross-regional sharing of public data to provide a solid foundation for enterprise AI applications. For the hard environment, accelerate the construction of digital infrastructure such as computing power facilities, 5G networks, and industrial internet to provide technical support for enterprise AI deployment. Simultaneously, implement incentive measures like tax reductions and special subsidies to lower AI application costs for enterprises.

Second, optimize environmental regulatory tools by effectively leveraging both government and market forces. When enterprises have comparable AI application levels, excessive environmental regulations and market monopolies alike hinder improvements in sustainable development performance. Governments should dynamically refine environmental regulatory approaches, shifting from "constraint-based" to "incentive-based" models. For instance, implement more market-oriented environmental policy tools. Increase the activity of emissions trading markets, allowing enterprises to offset part of their carbon quotas with AI-optimized emission reductions. Reduce compliance costs for enterprises. Meanwhile, strengthen antitrust regulation to prevent leading enterprises from monopolizing the green AI technology market, ensuring equal participation across all enterprise types. Only by appropriately leveraging both the "two hands" of government and market can we effectively enhance enterprises' sustainable development performance.

Third, enterprises, particularly management, should broaden their understanding of the commercial and environmental value of AI applications. First, when investing in AI applications, enterprises must prioritize the transformation of AI into green technologies. Green innovation is pivotal to AI's contribution to sustainable development outcomes. Enterprises should foster deep collaboration with research institutions. By sharing R&D expertise in optimizing supply chain management, reducing resource waste, and intelligent marketing, companies can achieve continuous innovation and transform research outcomes into tangible value. Governments can also establish green technology transfer and conversion platforms to accelerate the commercialization and scaled application of green innovations, thereby energizing corporate sustainability. Secondly, enterprises must recognize AI's capacity to enhance efficiency. AI applications should be viewed as a core driver for enhancing total factor productivity, not merely as a technical upgrade. Develop clear AI investment strategies, prioritizing areas that yield significant efficiency gains. Guide resources toward environmentally friendly technologies and processes to achieve synergistic optimization of efficiency and sustainability. Third, enterprises should focus on AI's role in facilitating information access. Improved information disclosure quality and reduced information asymmetry help enterprises navigate external changes and advance sustainable development performance. Therefore, businesses must integrate AI applications with financial and environmental data systems. Ensure AI technologies contribute to information sharing and system interoperability. Regulatory bodies should also adapt to evolving disclosure methods in the AI era. Establish disclosure rules and standards to build long-term digital trust.

Last, strengthen internal capacity building to prevent risks associated with AI applications. Companies should cultivate more talent with specialized AI knowledge and skills. Enhance environmental awareness training for executives and build reserves of multidisciplinary professionals. Conduct specialized training sessions focusing on how AI technologies can empower corporate sustainability. Provide targeted technical support and application consulting. Simultaneously, establish AI risk early-warning mechanisms. Monitor the energy consumption inherent to AI technologies, driving algorithm optimization to balance performance and energy usage. For emerging applications like Generative AI, establish ethics review committees. Clearly define boundaries and bottom lines for AI technology use to prevent risks and unsustainable development stemming from misuse.

6.3 Research Limitations

This study has the following limitations: (1) Limitations of causal inference. Although PSM-DID was employed to mitigate endogeneity issues, estimation biases stemming from "selection bias" cannot be entirely excluded [89]. Additionally, the experimental group policy may generate knowledge spillover or competitive effects on surrounding non-experimental group firms, thereby contaminating the control group. This leads to conservative DID estimation results. (2) Limitations in variable measurement. This study uses location within an AI policy zone as a proxy for corporate AI adoption. This relatively indirect measurement fails to precisely capture actual AI implementation levels or application domains. (3) Limitations in sample scope. The sample focuses on companies listed on the Shanghai and Shenzhen A-share markets from 2013 to 2023. The sample has limited coverage of enterprise types and industries and does not account for non-listed companies.

6.4 Research Outlook

According to the research limitations, future research can be carried out in the following aspects. First, future studies could employ more refined identification strategies and models, such as using spatial Durbin models to estimate AI policy spillover effects on neighboring firms. This would enable more accurate identification of the net effect of AI policies on sustainable development performance. Second, future research may employ more granular indicators, such as AI patent counts or survey data. Last, subsequent research could attempt to include more types of enterprises, such as small and medium-sized enterprises (SMEs) and non-listed companies. Additionally, cross-country comparative studies could be conducted to explore the similarities and differences in AI impacts under varying national institutional frameworks, market environments, and cultural contexts, thereby enhancing the comprehensiveness of the findings.

Author Contributions

Conceptualization, H.X.S.; methodology, H.X.S.; software, H.X.S.; validation, H.X.S. and R.C.Z.; formal analysis, H.X.S. and R.C.Z.; investigation, H.X.S.; resources, H.X.S.; data curation, H.X.S.; writing—original draft preparation, H.X.S.; writing—review and editing, H.X.S. and R.C.Z.; visualization, H.X.S.; supervision, H.X.S. and R.C.Z. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

All data in this study are available through the following channels:
https://www.cnipa.gov.cn/
https://global.csmar.com/
https://www.cnrds.com/
https://www.wind.com.cn/

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Notes

i. The LP method employs a C-D production function, using intermediate factor inputs as a proxy variable for estimating TFP. Specifically, intermediate factor inputs are measured as the sum of operating costs, administrative expenses, and sales expenses minus wages paid to employees.
ii. The collection standards for pollution discharge fees have changed with policy shifts. Since 2018, pollution discharge fees have been levied in the form of environmental protection taxes.
iii. According to the Guidelines for Industry Classification of Listed Companies revised by the China Securities Regulatory Commission in 2012 and the Catalog of Industry Classification Management for Environmental Protection Verification of Listed Companies published by the Ministry of Environmental Protection in 2008, industries with codes B06, B07, B08, B09, C15, C17, C18, C19, C22, C25, C26, C27, C28, C29, C31, C32, D44, and D45 are defined as heavily polluting industries. All others are classified as non-heavily polluting industries.

iv. Industry codes C26, C27, C28, C34, C35, C36, C37, C38, C39, C40, I63, I64, I65, M73, and M74 are defined as high-tech industries. All others are classified as non-high-tech industries.

v. Keywords include "environment" "environmental protection" "new energy" "clean energy" "ecology" "low-carbon" "sustainable" "energy conservation" and "green".

References

[1] Schaltegger, S., & Wagner, M. (Eds.). (2017). *Managing the business case for sustainability: The integration of social, environmental and economic performance*. Routledge. https://doi.org/10.4324/9781351280525

[2] Elkington, J. (1997). *Cannibals with forks: The triple bottom line of 21st century business*. Capstone. https://doi.org/10.1002/tqem.3310080106

[3] Friedman, M. (2007). The social responsibility of business is to increase its profits. In *Corporate ethics and corporate governance* (pp. 173-178). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-540-70818-6_14

[4] Porter, M. E., & Kramer, M. R. (2006). The link between competitive advantage and corporate social responsibility. *Harvard Business Review, 84*(12), 78-92. https://doi.org/10.1108/sd.2007.05623ead.006

[5] Brynjolfsson, E., & Mitchell, T. (2017). What can machine learning do? Workforce implications. *Science, 358*(6370), 1530-1534. https://doi.org/10.1126/science.aap8062

[6] Agrawal, A., Gans, J., & Goldfarb, A. (Eds.). (2019). *The economics of artificial intelligence: An agenda*. University of Chicago Press. https://doi.org/10.7208/chicago/9780226613475.001.0001

[7] Bughin, J., Hazan, E., Ramaswamy, S., Allas, T., Dahlstrom, P., Henke, N., & Trench, M. (2017). *Artificial intelligence: The next digital frontier?* McKinsey Global Institute. https://www.mckinsey.com/~/media/McKinsey/Industries/Advanced%20Electronics/Our%20Insights/How%20artificial%20intelligence%20can%20deliver%20real%20value%20to%20companies/MGI-Artificial-Intelligence-Discussion-paper.ashx?ref=faraday-blog

[8] Li, Y. X., Hu, Y. G., Wang, D., & et al. (2025). Painting the Future with AI: Artificial Intelligence and High-Quality Enterprise ESG Performance. *Contemporary Finance & Economics*, in press, 1-16. https://doi.org/10.13676/j.cnki.cn36-1030/f.20250227.001

[9] Xu, J. Y., Shen, H. Y., & Zhou, X. B. (2024). Artificial intelligence development and corporate ESG performance. *World Economy Studies*, (9), 120-134+137. https://doi.org/10.13516/j.cnki.wes.2024.09.006

[10] Zhong, W., Liu, Y., Dong, K., & Ni, G. (2024). Assessing the synergistic effects of artificial intelligence on pollutant and carbon emission mitigation in China. *Energy Economics, 138*, 107829. https://doi.org/10.1016/j.eneco.2024.107829

[11] Peng, Y., & Kong, Y. (2024). The Practical approach to the ethical principles of artificial intelligence: Inspiration from German AI ethics label. *Studies in Dialectics of Nature, 40*(2), 89-95. https://doi.org/10.19484/j.cnki.1000-8934.2024.02.013

[12] Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review, 96*(1), 108-116. https://academichelptoday.com/assets/documents/Artificial_Intelligence_for_the_Real_World_-_HBR.pdf

[13] Financial Stability Board. (2024). *The Financial Stability Implications of Artificial Intelligence*. FSB Report. https://www.fsb.org/uploads/P14112024.pdf

[14] Ahdadou, M., Aajly, A., & Tahrouch, M. (2024). Enhancing corporate governance through AI: a systematic literature review. *Technology Analysis & Strategic Management*, 1-14. https://doi.org/10.1080/09537325.2024.2326120

[15] Svetlana, N., Anna, N., Svetlana, M., Tatiana, G., & Olga, M. (2022). Artificial intelligence as a driver of business process transformation. *Procedia Computer Science, 213*, 276-284. https://doi.org/10.1016/j.procs.2022.11.067

[16] George, G., Haas, M. R., & Pentland, A. (2014). Big data and management. *Academy of Management Journal, 57*(2), 321-326. https://doi.org/10.5465/amj.2014.4002

[17] Vinuesa, R., Azizpour, H., Leite, I., Balaam, M., Dignum, V., Domisch, S., ... & Fuso Nerini, F. (2020). The role of artificial intelligence in achieving the Sustainable Development Goals. *Nature Communications, 11*(1), 233. https://doi.org/10.1038/s41467-019-14108-y

[18] IBM Institute for Business Value. (2022). *The quantitative impact of AI on financial functions: Improving process quality, reducing costs, and enhancing efficiency*. https://www.ibm.com/downloads/documents/cn-zh/107a02e97cc8fc76

[19] Elliot, S. (2011). Transdisciplinary perspectives on environmental sustainability: a resource base and framework for IT-enabled business transformation. *Management Quarterly*, 197-236. https://doi.org/10.2307/23043495

[20] Jin, X. Y., Zuo, C. J., Fang, M. Y., et al. (2024). Measurement Problem of Enterprise Digital Transformation:New Methods and Findings Based on Large Language Models. *Economic Research Journal, 59*(3), 34-53. https://doi.org/10.19602/j.chinaeconomist.2025.03.04

[21] Zhou, J. T., Xi, Y. Q., Zhou, Y. Y., & et al. (2020). Big data, artificial intelligence, and innovation in fiscal and tax services. *China Soft Science*, (8), 69-77. https://doi.org/10.3969/j.issn.1002-9753.2020.08.007

[22] Dian, J., Li, S., & Song, T. (2025). Achieving the synergy of pollution and carbon emission reductions: Can artificial intelligence applications work?. *China Economic Review, 91*, 102389. https://doi.org/10.1016/j.chieco.2025.102389

[23] Wang, H. H., Tan, Q. Y., & Li, Y. (2023). Digital Technology Application, Green Innovation and Enterprise Sustainable Development Performance: The Moderating Effect of Institutional Pressure. *Science & Technology Progress and Policy, 40*(7), 124-135. https://doi.org/10.6049/kjjbydc.2022060734

[24] Zhu, S. W., Liang, R., & Lv, K. J. (2024). The Impact of Artificial Intelligence and Corporate Digital Responsibility on Corporate Social Performance: Evidence Based on ESG Performance of Chinese Listed Firms. *Journal of Xi'an University of Finance and Economics, 37*(6), 64-79. https://doi.org/10.19331/j.cnki.jxufe.2024.06.003

[25] Xiu, Y. M. (2025). In the era of artificial intelligence: New ideas for social development—a review of The Sociology of Artificial Intelligence. *Journal of the Chinese Society of Education*, (8), 125. https://kns.cnki.net/kcms2/article/abstract?v=bJ89lKU86K_-AOGndizUrZHVqUH372oamT2LAhDtnD-EIiMeUTbYaYFI5hOqUvkkeXSabdfVqAlJX0iyYr9FeZ3DcPVCMom1JSe_POCpupvWitGUBPQsZES1R6yaDSAgHR6uqdL9ASUQOk6c0j06H5hMj2QYsWqIJQ2-ez1agGDrkQrMho4nCw==&uniplatform=NZKPT&language=CHS

[26] Djeffal, C. (2019). Sustainable development of artificial intelligence (SAID). *Djeffal C: Sustainable Development of Artificial Intelligence (SAID), 4*, 186-192. https://mediatum.ub.tum.de/doc/1584484/1584484.pdf

[27] Xie, X. M., & Zhu, Q. W. (2021). How can green innovation resolve the dilemmas of "harmonious coexistence". *Management World, 37*(1), 128-149, 9. https://doi.org/10.19744/j.cnki.11-1235/f.2021.0009

[28] Xie, X. M., Huo, J. G., & Wang, H. W. (2019). The relationship between green process innovation and financial performance in the manufacturing industry. *Science Research Management, 40*(3), 63-73. https://doi.org/10.19571/j.cnki.1000-2995.2019.03.007

[29] Khaksar, E., Abbasnejad, T., Esmaeili, A., & Tamošaitienė, J. (2016). The effect of green supply chain management practices on environmental performance and competitive advantage: a case study of the cement industry. *Technological and Economic Development of Economy, 22*(2), 293-308. https://doi.org/10.3846/20294913.2015.1065521

[30] Cheng, C. C., Yang, C. L., & Sheu, C. (2014). The link between eco-innovation and business performance: a Taiwanese industry context. *Journal of Cleaner Production, 64*, 81-90. https://doi.org/10.1016/j.jclepro.2013.09.050

[31] Seman, N. A. A., Govindan, K., Mardani, A., Zakuan, N., Saman, M. Z. M., Hooker, R. E., & Ozkul, S. (2019). The mediating effect of green innovation on the relationship between green supply chain management and environmental performance. *Journal of Cleaner Production, 229*, 115-127. https://doi.org/10.1016/j.jclepro.2019.03.211

[32] Acemoglu, D., & Restrepo, P. (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. *American Economic Review, 108*(6), 1488-1542. https://doi.org/10.1257/aer.20160696

[33] Misch, F., Park, B., Pizzinelli, C., & Sher, G. (2025). *Artificial Intelligence and Productivity in Europe*. IMF Working Paper. https://doi.org/10.5089/9798229006057.001

[34] Han, X. C., & Chen, F. F. (2023). Digital transformation and total factor productivity: Mediation effect based on green innovation. *Journal of Harbin University of Commerce (Social Science Edition)*, (4), 71-87. https://kns.cnki.net/kcms2/article/abstract?v=fvwDbTJIyzTGjTxRtZguLhxqx3M_deXG88MFFHhrqc4MVXvV_J8Ca9q2W1AJY6ElhtKgHRXS0vA-fEhsvjkbkzzAMO6G-yJYEyZ-y_FySJftyt_99M8e9fkbbO5DcJlZjo_29EHa6X0HY8CajUAFVH8K2WpryI4aMwU4X19nAhKYF6phTe2bAw==&uniplatform=NZKPT&language=CHS

[35] Ghisetti, C., & Quatraro, F. (2017). Green technologies and environmental productivity: A cross-sectoral analysis of direct and indirect effects in Italian regions. *Ecological Economics, 132*, 1-13. https://doi.org/10.1016/j.ecolecon.2016.10.003

[36] Zhang, Z. B., & Ou, L. (2024). Is service-oriented manufacturing beneficial for enhancing supply chain resilience? *Journal of Hunan University of Science and Technology (Social Science Edition), 27*(4), 63-72. https://doi.org/10.1016/j.ecolecon.2016.10.003

[37] Han, E., Yin, D., & Zhang, H. (2023). Bots with feelings: Should AI agents express positive emotion in customer service? *Information Systems Research, 34*(3), 1296-1311. https://doi.org/10.1287/isre.2022.1179

[38] Yang, S. P., & Yu, L. S. (2023). Opportunities and Challenges Brought by ChatGPT-based Generative AI to Tax Administration. *Taxation Research*, (6), 16-20. https://doi.org/10.19376/j.cnki.cn11-1011/f.2023.06.013

[39] Liu, S., & Cao, Y. J. (2025). Digital Carbon Neutralization: An Empirical Study on the Dual Effects of Artificial Intelligence in Promoting Industrial Carbon Reduction. *Journal of Jiangsu University (Social Science Edition), 27*(2), 26-39. https://doi.org/10.13317/j.cnki.jdskxb.2025.12

[40] Edwards, J. S., Duan, Y., & Robins, P. C. (2000). An analysis of expert systems for business decision making at different levels and in different roles. *European Journal of Information Systems, 9*(1), 36-46. https://doi.org/10.1057/palgrave.ejis.3000344
[41] Richardson, A. J., & Welker, M. (2001). Social disclosure, financial disclosure and the cost of equity capital. *Accounting, Organizations and Society, 26*(7-8), 597-616. https://doi.org/10.1016/S0361-3682(01)00025-3
[42] Seligsohn, D., Liu, M., & Zhang, B. (2018). The sound of one hand clapping: Transparency without accountability. *Environmental Politics, 27*(5), 804-829. https://doi.org/10.1080/09644016.2018.1452522
[43] Arowoshegbe, A. O., Emmanuel, U., & Gina, A. (2016). Sustainability and triple bottom line: An overview of two interrelated concepts. *Igbinedion University Journal of Accounting, 2*(16), 88-126. https://www.researchgate.net/publication/322367106
[44] Jiang, W., Chai, H., Shao, J., & Feng, T. (2018). Green entrepreneurial orientation for enhancing firm performance: A dynamic capability perspective. *Journal of Cleaner Production, 198*, 1311-1323. https://doi.org/10.1016/j.jclepro.2018.07.104
[45] Mer, A., & Virdi, A. S. (2025). The influence of artificial intelligence on personal and corporate finance: A comprehensive literature review with prospects for future research. *Financial Landscape Transformation: Technological Disruptions*, 253-268. https://doi.org/10.1108/978-1-83753-750-120251014
[46] Acemoglu, D., & Restrepo, P. (2019). Artificial Intelligence, Automation, and Work: Daron Acemoglu and Pascual Restrepo. In *The economics of artificial intelligence: An agenda*. University of Chicago Press. https://doi.org/10.7208/chicago/9780226613475.003.0008
[47] Magazzino, C., Mele, M., Morelli, G., & Schneider, N. (2021). The nexus between information technology and environmental pollution: Application of a new machine learning algorithm to OECD countries. *Utilities Policy, 72*, 101256. https://doi.org/10.1016/j.jup.2021.101256
[48] Endrikat, J., Guenther, E., & Hoppe, H. (2014). Making sense of conflicting empirical findings: A meta-analytic review of the relationship between corporate environmental and financial performance. *European Management Journal, 32*(5), 735-751. https://doi.org/10.1016/j.emj.2013.12.004
[49] Alexopoulos, I., Kounetas, K., & Tzelepis, D. (2018). Environmental and financial performance. Is there a win-win or a win-loss situation? Evidence from the Greek manufacturing sector. *Journal of Cleaner Production, 197*, 1275-1283. https://doi.org/10.1016/j.jclepro.2018.06.302
[50] Zang, J., & Li, Y. (2017). Technology capabilities, marketing capabilities, and innovation ambidexterity. *Technology Analysis & Strategic Management, 29*(1), 23-37. https://doi.org/10.1080/09537325.2016.1194972
[51] Wu, Z., Zhai, Y., & Zeng, Y. (2024). Corporate sustainability performance assessment under the low carbon city pilot policy framework. *Shanghai Journal of Economics*, (11), 53-64+91. https://doi.org/10.19626/j.cnki.cn31-1163/f.2024.11.006
[52] Yao, J., Zhang, K., Guo, L., & Feng, X. (2024). How does artificial intelligence improve firm productivity? Based on the perspective of labor skill structure adjustment. *Journal of Management World, 40*(2), 101-116. https://doi.org/10.19744/j.cnki.11-1235/f.2024.0018
[53] Acemoglu, D., Anderson, G., Beede, D. N., Buffington, C., Childress, E. E., Dinlersoz, E. M., ... & Zolas, N. (2022). *Automation and the workforce: A firm-level view from the 2019 annual business survey* (Vol. 30659). National Bureau of Economic Research. https://doi.org/10.3386/w30659
[54] Mann, K., & Püttmann, L. (2023). Benign effects of automation: New evidence from patent texts. *Review of Economics and Statistics, 105*(3), 562-579. https://doi.org/10.1162/rest_a_01083
[55] Yu, S. L., & Shi, H. (2025). The impact of artificial intelligence policies on corporate ESG performance: Empirical evidence from the national pilot zones for artificial intelligence innovation and application. *Western Forum, 35*(4), 52-67. https://doi.org/10.3969/j.issn.1674-8131.2025.04.004
[56] Wang, W., Wang, L., Sun, Z., & Ma, D. (2025). Can carbon emission trading improve corporate sustainability? An analysis of green path and value transformation effect of pilot policy. *Clean Technologies and Environmental Policy, 27*(3), 1505-1520. https://doi.org/10.1007/s10098-024-02910-2
[57] Sun, Y. (2024). The impact of integrated reporting approach on sustainability performance of state-owned enterprises. *Environment, Development and Sustainability*, 1-36. https://doi.org/10.1007/s10668-024-05633-y
[58] Jin, X. Y., & Zhang, W. F. (2023). Artificial intelligence and enterprise pollution reduction: Environmental effects of intelligent governance. *China Population, Resources and Environment, 33*, 138-145. https://doi.org/10.12062/cpre.20230334
[59] Feng, W. X. (2024). Artificial Intelligence and Corporate Financial Asset Allocation: Empirical Evidences from the National AI Innovation and Application Pioneer Zone. *Contemporary Finance & Economics*, (4), 141. https://doi.org/10.13676/j.cnki.cn36-1030/f.20240219.001

[60] Levinsohn, J., & Petrin, A. (2003). Estimating production functions using inputs to control for unobservables. *The Review of Economic Studies, 70*(2), 317-341. https://doi.org/10.1111/1467-937X.00246
[61] Zhong, J., Ding, Y. F., Ling, Z. A., & Wei, Y. J. (2025). AI Applications and Diversification of Enterprise Customer Configuration: A Quasi-natural Experiment Based on AI Innovation Application Pilot Zone. *Foreign Economics & Management, 47*(06), 18-35. https://doi.org/10.16538/j.cnki.fem.20241122.301
[62] Levinson, A. (1996). Environmental regulations and manufacturers' location choices: Evidence from the Census of Manufactures. *Journal of Public Economics, 62*(1-2), 5-29. https://doi.org/10.1016/0047-2727(96)01572-1
[63] Li, L., & Tao, F. (2012). Selection of optimal environmental regulation intensity for Chinese manufacturing industry—Based on the green TFP perspective. *China Industrial Economics, 5*(5), 70-82. https://doi.org/10.19581/j.cnki.ciejournal.2012.05.006
[64] Kale, J. R., & Loon, Y. C. (2011). Product market power and stock market liquidity. *Journal of Financial Markets, 14*(2), 376-410. https://doi.org/10.1016/j.finmar.2010.10.003
[65] Jacobson, L. S., LaLonde, R. J., & Sullivan, D. G. (1993). Earnings losses of displaced workers. *The American Economic Review*, 685-709. https://doi.org/10.17848/wp92-11
[66] Li, J., Wang, K., & Mei, Y. (2024). State-owned capital participation and corporate environmental, social, and governance performance: Evidence from Chinese private firms. *Journal of the Knowledge Economy*, 1-28. https://doi.org/10.1007/s13132-024-02432-8
[67] Nunn, N., & Qian, N. (2014). US food aid and civil conflict. *American Economic Review, 104*(6), 1630-1666. https://doi.org/10.1257/aer.104.6.1630
[68] Wang, J., Sun, H., & Liao, Z. L. (2025). Study on the Mechanisms of Artificial Intelligence Technology Empowering Dual Carbon Practice Performance. *Science & Technology Progress and Policy*, 1-13. https://link.cnki.net/urlid/42.1224.G3.20250723.1005.004
[69] Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics, 225*(2), 254-277. https://doi.org/10.1016/j.jeconom.2021.03.014
[70] Borusyak, K., Hull, P., & Jaravel, X. (2022). Quasi-experimental shift-share research designs. *The Review of Economic Studies, 89*(1), 181–213. https://doi.org/10.1093/restud/rdab030
[71] Bodory, H., Huber, M., & Lafférs, L. (2022). Evaluating (weighted) dynamic treatment effects by double machine learning. *The Econometrics Journal, 25*(3), 628-648. https://doi.org/10.1093/ectj/utac018
[72] Zhang, X. E., & Yu, Y. B. (2025). The impact of digital transformation on the sustainable performance of heavy-polluting enterprises. *Science & Technology Progress and Policy, 42*(2), 82–92. https://doi.org/10.6049/kjjbydc.2024050176
[73] Chao, X. J., & Shen, L. (2025). The Impact of Artificial Intelligence Technology on Manufacturing Enterprises' Green Innovation Efficiency from the Perspective of Innovation Value Chain. *Economic Perspectives*, (4), 50–67.
[74] Jiang, T. (2022). Mediating Effects and Moderating Effects in Causal Inference. *China Industrial Economics*, 5, 100–120. https://doi.org/10.3969/j.issn.1006-480X.2022.05.007
[75] Wang, Y., Liu, Y., & Chen, X. H. (2025). Green technology innovation, ESG ratings and corporate sustainable performance: Empirical evidence from listed semiconductor companies in China. *International Review of Economics & Finance, 99*, 104061. https://doi.org/10.1016/j.iref.2025.104061
[76] Acemoğlu, D., & Restrepo, P. (2016). *The race between machines and humans: Implications for growth, factor shares and jobs*. https://doi.org/10.3386/w22252
[77] Deng, B., & Guo, J. H. (2011). An analysis of the dynamic impact effect of technological progress on sustainable development. *Enterprise Economy, 30*(2), 9-12. https://doi.org/10.13529/j.cnki.enterprise.economy.2011.02.008
[78] Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management, 58*(3), 103434. https://doi.org/10.1016/j.im.2021.103434
[79] Wamba-Taguimdje, S. L., Fosso Wamba, S., Kala Kamdjoug, J. R., & Tchatchouang Wanko, C. E. (2020). Influence of artificial intelligence (AI) on firm performance: the business value of AI-based transformation projects. *Business Process Management Journal, 26*(7), 1893-1924. https://doi.org/10.1108/BPMJ-10-2019-0411
[80] Xue, Y., Jiang, C., Guo, Y., Liu, J., Wu, H., & Hao, Y. (2022). Corporate social responsibility and high-quality development: Do green innovation, environmental investment and corporate governance matter?. *Emerging Markets Finance and Trade, 58*(11), 3191-3214. https://doi.org/10.1080/1540496X.2022.2034616
[81] Gröger, J., Behrens, F., Gailhofer, P., & Hilbert, I. (2025). *Environmental impacts of artificial intelligence* (Prepared for Greenpeace e.V.). Öko-Institut Consult GmbH. https://www.greenpeace.de/publikationen/umweltauswirkungen-kuenstlicher-intelligenz
[82] Wang, H., Lin, W., & Xie, R. (2022). Environmental backgrounds of executives and green investor entry. *Journal of Quantitative & Technological Economics, 39*(12), 173-194. https://doi.org/10.13653/j.cnki.jqte.2022.12.009

[83] Singla, A., Sukharevsky, A., Yee, L., Chui, M., & Hall, B. (2025). *The state of AI: How organizations are rewiring to capture value*. McKinsey & Company. https://sitic.org/wordpress/wp-content/uploads/The-state-of-AI-How-organizations-are-rewiring-to-capture-value.pdf

[84] Xiao, H. J., Shen, H. T., & Zhou, Y. K. (2024). Customer Digitalization,Supplier ESG Performance and Supply Chain Sustainability. *Economic Research Journal, 59*(03), 54-73. https://kns.cnki.net/kcms2/article/abstract?v=fvwDbTJIyzQYU_xBvcymYH_6sBD2StY0pU_AQAqx3YIPWKGh4pucGyOcGsocZrJTOhl-bBu9Y3mvNZa2zxNL4jSe5zFk42muYJgLv6xYBscLjjIRffoDjjt-l3k6z9rggRJjoqQDROTEAT1oOFyBEYhryjQbQXIFT1TgKwYPPp3XrjsL84ZZfA==&uniplatform=NZKPT&language=CHS

[85] Wang, A. P., Chen, M., & Hu, H. F. (2024). Impact of Pilot Zones for Green Finance Reform and Innovations on Corporate Green Transformation:An Analysis Based on Strategic Orientation and Innovation Actions of Enterprises. *Nankai Economic Studies*, (12), 187-205. https://doi.org/10.14116/j.nkes.2024.12.011

[86] Meng, M. M., Tan, X. Y., Liu, S. R., et al. (2023). Research on the Impact of ESG Performance on Green Innovation. *Journal of Technology Economics, 42*(07), 13-24. https://doi.org/10.3969/j.issn.1002-980X.2023.07.003

[87] Xie, J., Hou, Y. R., & Huang, J. (2025). Short-term Inhibition Effect of Market Integration on Enterprises' Long-term Investment And the Solution of That. *China Business and Market, 39*(08), 98-112. https://doi.org/10.14089/j.cnki.cn11-3664/f.2025.08.008

[88] Rasheed, M. Q., Yuhuan, Z., Haseeb, A., Ahmed, Z., & Saud, S. (2024). Asymmetric relationship between competitive industrial performance, renewable energy, industrialization, and carbon footprint: Does artificial intelligence matter for environmental sustainability?. *Applied Energy, 367*, 123346. https://doi.org/10.1016/j.apenergy.2024.123346

[89] Zhou, Q. (2021). The Formative Mechanism of Journalistic Credibility in the Context of Digital Media Consumption. *Journalism Research*, (09), 40-58, 118. https://doi.org/10.20050/j.cnki.xwdx.2021.09.005