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AI-driven green governance: Assessing the impact of artificial intelligence on corporate sustainability performance

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ABSTRACT

As global climate change and sustainability challenges intensify, corporate green governance has become a key strategy for enhancing competitiveness. The rapid advancement of artificial intelligence (AI) offers new momentum for green governance innovation. Using panel data on Chinese listed firms from 2009 to 2023, this study examines how AI adoption influences green governance performance. The findings reveal that AI significantly enhances environmental performance, lowers ecological costs, and promotes sustainable innovation. The results remain robust across multiple specifications, with stronger effects observed in state-owned enterprises, financially constrained firms, and ISO14001-certified companies. Employing Bartik instrumental variables mitigates potential endogeneity concerns. Mechanism analysis demonstrates that AI fosters green governance through improvements in asset efficiency, market valuation, and cash flow management. These insights underscore the strategic importance of AI-driven green governance as a pathway toward corporate sustainability and competitive advantage.

Introduction

Driven by technological breakthroughs in deep neural networks and language models, AI has rapidly developed, becoming a significant force for scientific and technological progress, industrial transformation, and productivity improvement (Acemoglu & Restrepo, 2020), profoundly reshaping human production and lifestyle. Internationally, the EU's "White Paper on Artificial Intelligence, " the US's "National Artificial Intelligence R&D Strategic Plan, " and Japan's "Artificial Intelligence Strategy 2022" all emphasize the role of AI in sustainable development and green innovation. With the acceleration of scientific and technological revolution and industrial transformation, AI demonstrates broad potential as a core driver of this new round of change. Robotics, image recognition, and natural language processing have been widely used in the Fourth Industrial Revolution (Frey & Osborne, 2017).

AI has strengthened corporate green governance by optimizing energy use, reducing risks, and improving data processing. Machine learning enables real-time analysis of emissions, while big data systems enhance monitoring accuracy (Bibri et al., 2024). Beyond passive monitoring, AI actively generates knowledge by uncovering patterns and solutions that drive green innovation and strategic transformation. It has reshaped organizational structures and decision-making processes (Sklavos et al., 2024), minimized misalignments, enhanced collaboration and information exchange, and fostered green synergies that advance sustainable industrial development. Nevertheless, the role of AI in corporate green governance remains largely experimental, as most existing research has concentrated on theoretical discussions and case studies without establishing a systematic analytical framework. (Zhao et al., 2022; Dwivedi et al., 2021). Variations in goals, resources, data, costs, and governance lead to heterogeneous outcomes. Yet AI's power in computing and optimization shows transformative potential in resource allocation, processes, and monitoring (Challoumis, 2024).

This study contributes to three industry fronts. First, methodologically, it constructs a rigorous econometric model using up-to-date firm-level panel data. By employing Bartik instrumental variables to establish causality between adoption of AI and improved green governance performance, it effectively addresses endogeneity, thereby enhancing the robustness and theoretical value of the findings. Second, unlike earlier research that were often confined to theoretical discussion or case studies, this paper empirically investigates AI's impact on listed companies' green governance at the corporate level, providing more generalizable evidence. Finally, it moves beyond AI's monitoring and optimization functions to highlight its role as a knowledge generator, mining and integrating environmental data to produce insights that

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drive innovative green strategies—an aspect largely underexplored in the existing literature.

Literature review and theoretical hypothesis

Literature review

Existing research primarily examines the role of artificial intelligence in improving energy efficiency, reducing emissions, and promoting green development and innovation, yielding substantial empirical findings. In the realm of energy conservation and emission reduction, industrial robots enable real-time monitoring of energy consumption and emissions, thereby curbing excessive discharges and enhancing the efficiency of resource utilization (Soori et al., 2023). Simultaneously, they enable clean production and improvements in total factor productivity through precise energy management (Ibekwe et al., 2024). AI can also reduce pollution emissions by improving management efficiency, lowering costs, and driving clean-energy innovation. Furthermore, it enhances urban carbon emission efficiency through knowledge spillovers facilitated by industrial agglomeration effects.

Regarding green development, existing research generally recognizes AI as a technological advancement that boosts automation and production efficiency, thereby promoting green development efficiency. Its mechanisms encompass both direct promotion of green development as well as optimization of industrial structure and upgrading. Related findings indicate that industrial robot applications enhance regional ecological efficiency through technological progress, energy structure optimization, and industrial agglomeration effects (Yu et al., 2022). AI further supports urban green development via innovation effects, labor substitution, and investments directed to emission reduction efforts.

Regarding green innovation, AI stimulates corporate innovation vitality and accumulates green outcomes by enhancing production certainty, optimizing resource allocation, and mitigating risks (Chowdhury et al., 2023). Its introduction also leverages human capital advantages, optimizes governance structures, and promotes corporate green innovation. However, some studies suggest AI's impact on green innovation is phased, with significant short-term effects but potential diminishing returns over the long term (Zhao et al., 2022; Nishant, 2020). Overall, AI plays a crucial role in enhancing resource efficiency, optimizing industrial structures, and driving green technological innovation (Chotia et al., 2024; Nahar, 2024). Along production chains, it enables green process innovation—such as improving efficiency, reducing carbon emissions, and promoting recycling (Cicerone et al., 2023; Chotia et al., 2024). In product development, AI improves quality, lowers R&D costs, and drives business growth through iterative refinement (Babina et al., 2024). However, existing research has predominantly focused on macro-level perspectives, with limited exploration of green governance mechanisms at the micro level of individual enterprises. Therefore, further investigation at the firm level is warranted.

Theoretical hypothesis

In current corporate environment, the rapid development of AI has brought far-reaching implications for listed companies in the field of green governance. Green governance, as an important component of corporate sustainability, aims to enhance corporate social responsibility and economic competitiveness by improving resource efficiency, reducing environmental pollution, and promoting the development of eco-friendly products. AI can help firms better understand and monitor their environmental impacts through data mining and analytics (Benzidia et al., 2021). For example, machine learning algorithms can efficiently process extensive environmental datasets to identify possible environmental risks and resource wastage in business operations. This precise risk identification not only reduces firms' environmental burdens but also enhances their green governance performance. Empirical evidence indicates that companies employing AI for environmental data analysis generally achieve superior outcomes in carbon emission control and resource management (Su et al., 2020). Moreover, the application of AI in decision-support systems substantially strengthens the coherence and efficiency of corporate green decision-making. Through intelligent algorithms, firms can simulate alternative operational scenarios and evaluate their respective environmental impacts to formulate more sustainable business strategies. This data-driven decision-making process reduces the interference of human factors in traditional decision-making and improves the transparency and rationality of decisions. According to existing research, companies that utilize AI technology for decision-making have better records in terms of environmental policy compliance and implementation effectiveness (Zhao & Gómez Fariñas, 2023). AI technology is also crucial in the optimization of the production process either, and through intelligent production scheduling and resource allocation, companies are able to maximize production efficiency while reducing energy consumption and waste emissions. This win–win effect not only generates economic benefits but also delivers positive outcomes in environmental protection. Based on the analysis of existing literature and the research objectives of this study, the application of AI influences the green governance performance of listed firms through three key dimensions: total asset turnover, price-to-book ratio, and cash flow ratio. The influence of AI implementation on the green governance performance of listed companies involves complex mechanisms and multi-dimensional paths. The role of AI technology in improving revenue generating capacity, future profitability and growth potential, and short-term solvency becomes the core theoretical hypothesis of the study through the three key financial indicators, namely, total asset turnover, price-to-book ratio, and cash flow ratio. The synergy of the three effects helps companies invest resources in green aspects, thus improving the green governance performance of listed companies.

Total asset turnover rate improvement effect

AI technology can augment the allocation of enterprise resources, thus improving the total asset turnover rate. Through machine learning and big data analysis, enterprises can precisely forecast market demand, streamline production scheduling, and improve inventory control, reduce resource waste, and thus improve total asset turnover. The improved total asset turnover provides enterprises with more disposable resources, releasing more capital and resources and enhancing their ability to invest in green governance, which corporate enterprises are able to use for green technology research and environmental projects, such as cleaner production technology and the development of green building materials (Li et al., 2021). AI can help corporate managers better understand shifts in market demand, consumer preferences, and raw material supply chains through big data analysis and machine learning, helping companies plan production and inventory. When the effectiveness of resource distribution within the enterprise is improved and the liquidity of operating funds is enhanced, enterprises can more actively invest in green technology research, environmental protection facilities construction and other fields, thus enhancing green governance performance while realizing environmental objectives. In addition, AI technology can also directly support green governance. AI can be used for carbon emission monitoring, energy use optimization, etc., to help enterprises better achieve environmental goals. This green transformation not only reduces the risk cost of enterprises in terms of environmental violations, but also enhances their social reputation and long-term financial performance, forming a positive cycle of green governance and financial performance (Zhu et al., 2021). Therefore, in light of this, the study puts forward the following hypothesis.

Hypothesis 1. The application of AI helps improve the total asset turnover ratio and green governance performance of listed companies.

Price-to-book ratio (P/B ratio) enhancement effect

The use of AI can improve the operational efficiency and innovation of companies and drive the P/B ratio. Predictive algorithms driven by AI can facilitate firms to seize market opportunities and improve profitability, and these factors are reflected in investors' higher assessment of firm value, which in turn boosts the P/B ratio. The increase in P/B ratio enhances the ability and willingness of firms to invest in green governance (Masditok et al., 2024). P/B ratio, as a capital market's evaluation index of a firm's future growth potential, is usually closely related to the firm's profitability and innovation capacity. The increase of P/B ratio as an indicator of capital market's evaluation of firms' future growth potential helps firms obtain more external capital support. Enterprises with high P/B ratios usually face higher social responsibility expectations and stricter ESG considerations, and this pressure prompts enterprises to place greater emphasis on the structure of green governance (Ding, 2022). The direct role of AI in green governance further reinforces the performance improvement, which not only reduces the environmental compliance risk of enterprises, but also further promotes their social reputation and financial performance, shapes favorable public images, and feeds back into the sustained growth of the price-to-book ratio. This positive financial performance feedback further promotes the sustained growth of the P/B ratio, forming a positive cycle between the P/B ratio, green governance performance and financial performance. In light of this, the study puts forward the following hypothesis.

Hypothesis 2. The application of AI helps to increase the price-to-book ratio and improve the green governance performance of listed companies.

Cash flow ratio reduction effect

Operational efficiencies optimized by AI in inventory management, production planning, and supply chain operations can reduce short-term capital usage and make companies more liquid, resulting in lower cash flow ratios. The cash flow ratio serves as a key indicator of a firm's capacity to meet short-term financial obligations and maintain liquidity. A lower cash flow ratio often reflects more efficient fund utilization, as it indicates a reduction in cash retained for day-to-day operations. Optimized flow of funds allows a firm to be more flexible and less reliant on short-term funds rather than relying too much on short-term funds tied up, thus lowering the cash flow ratio. Lower cash flow ratios mean that firms are able to invest more funds in long-term strategic projects, including green governance-related areas, promoting green technology investments and environmental governance measures (Zellweger, 2007). AI indirectly supports green governance by lowering the cash flow ratio while directly improving governance efficiency, and this influence mechanism forms a positive cycle, resulting in the mutual promotion and optimization between financial liquidity and green governance performance. In light of this, the study puts forward the following hypothesis.

Hypothesis 3. The application of AI helps to reduce the cash flow ratio and improve the green governance performance of listed companies.

Research data

Data sources

With a view to study the impact of the application of AI on the green governance performance of listed companies, this paper in terms of AI collects data from the annual reports and patent reports of enterprises, which are acquired from the Cathay Pacific database (CSMAR). The data on green governance performance of listed companies come from CSM ESG, annual reports of listed companies, social responsibility reports, and sustainability reports. In order to ensure the reliability of the data, this paper adopts a series of treatments: (1) excluding enterprises in the financial industry; (2) excluding samples whose enterprises are in ST and *ST status in the current year; (3) excluding samples with serious missing data.

Description of variables

Explained variable: Green governance performance of listed companies

The green governance performance of listed companies serves as a key indicator for measuring their overall performance in environmental protection, sustainable development, green innovation, and social responsibility. Referring to the analytical study of Wang and Xiao (2024), the Janis-Fadner coefficient (J-F coefficient) is used to measure the green governance performance based on positive and negative scores of a company's green governance practices. The value of the GGP is in the range of [−1, 1], and larger values mean better green governance performance. GGP is calculated as follows (3–1):

$$GGP = \begin{cases} (p^2 - p \times \ |q|) \div r^2, \ if\ p > |q| \\ (p \times |q| - q^2) \div r^2, \ if\ p < |q| \\ 0, \ if\ p = |q| \end{cases} \tag{3–1}$$

p represents the score for meeting positive criteria (1 point per criterion), q represents the score for meeting negative criteria (−1 point per criterion), and r is the sum of the absolute values of both, i.e., $r = p + |q|$.

Specifically, p is defined as actions or disclosures that contribute to environmental sustainability, such as an environmental governance score in the top 30 of the sample, environmental honors or awards, or ISO 14,001 certification. q includes those that undermine sustainability goals, such as substandard pollutant emission scores, lack of emission reduction measures, or environmental violations.

Explanatory variable: AI applications

We employ text mining techniques to identify AI-related discourse among publicly listed firms. Specifically, the methodology involves preprocessing corporate annual and patent reports—through PDF-to-text conversion, word segmentation, stopword removal, and stemming—and subsequently constructing a keyword list derived from authoritative AI literature and terminology databases. This list includes core terms such as "artificial intelligence, " "machine learning, " "deep learning, " "natural language processing, " and "autonomous driving." Subsequently, combining exact and fuzzy matching, relevant patent information is extracted from the text, and multiple expressions of the same term are normalized. To mitigate the skewness effect of high-frequency words, the occurrence frequency of each term is incremented by 1 and then log-transformed to create a comparable metric (Wang et al., 2024). This approach effectively identifies firms' patent accumulation and discourse patterns related to AI; however, it captures only AI-related textual expressions rather than the depth or quality of actual application. Nonetheless, text mining excels at processing large volumes of unstructured data, thereby enhancing analytical efficiency and providing robust empirical support for research (Hassani et al., 2020). Building on this foundation, this paper employs the logarithm of keyword frequency plus one as an AI application metric. Future research may validate this approach by integrating more direct measurement methods (e.g., AI attention or engagement metrics).

Control variables

In order to ensure the accuracy of the study and with reference to existing studies, this paper adds a series of control variables, i.e., variables that have a crucial impact on the green governance performance of listed companies into the model to ensure an accurate assessment of the effect of AI application. The following control variables are selected in this paper: Enterprise size (SIZE), the equity multiplier (EM), gearing ratio (LEV), return on equity (ROE), firm age (AGE), shareholding concentration - the proportion of shares held by the largest shareholder (TOP1), gross profit margin (GPR). The measurements and sources of variables are shown in Table 1.

Table 1
Variable Description.

Variable	Type	Measurement Method	Data Source
Green Governance Performance (GGP)	Dependent Variable	Janis-Fadner coefficient (J-F coefficient)	CSMAR,CSM ESG, annual reports of listed companies, social responsibility reports, and sustainability reports
AI Applications	Explanatory Variable	Text mining of patent information to extract AI-related terms. Keywords include AI, machine learning, autonomous driving, NLP, etc. Logarithmic processing of the number of keywords + 1.	
Enterprise Size (SIZE)	Control Variable	Logarithm of total assets	
Equity Multiplier (EM)	Control Variable	Total assets / Shareholders' equity	
Gearing Ratio (LEV)	Control Variable	Total debt / Total assets	
Return on Equity (ROE)	Control Variable	Net income / Shareholders' equity	
Enterprise Age (AGE)	Control Variable	Number of years since the company was established	
Shareholding Concentration (TOP1)	Control Variable	Proportion of shares held by the largest shareholder (Top 1 shareholder)	
Gross Profit Margin (GPR)	Control Variable	(Revenue - Cost of Goods Sold) / Revenue	

Model

To assess the impact of AI application on the green governance performance of listed companies, this paper adopts the panel data of listed companies in China, and this paper chooses the fixed effect model for regression, and the specific model settings (3–2) are as follows:

$$GGP_{it} = \beta_0 + \beta_1 AI_{it} + X_{it}\gamma + \sigma_j + \sigma_t + \varepsilon_{it} \tag{3–2}$$

Where i denotes the listed company; t denotes the year; GGP is an explanatory variable, denoting the green governance performance of listed companies; ai is a core explanatory variable, denoting the application of AI; X_{it} is a set of control variables; σ_j is an industry fixed effect; σ_t is a time fixed effect; and ε_{it} is a random perturbation term.

The following clarification needs to be made in regard of the model configuration shown above: this paper adopts industry fixed effects instead of individual fixed effects. Therefore, the subscript of the fixed effect is set to j. On the one hand, the size of the sample is adequate to compensate for the "roughness" in this regard to a certain extent. On the other hand, the use of AI is uniform at the industry level, i.e., the differences are mainly inter- rather than intra-industrial.

Descriptive statistics

Prior to the regression analysis, this study first demonstrates the basic characteristics of the data by performing descriptive statistics on the main variables. Descriptive statistics include the mean, standard deviation, minimum, and maximum values of each variable in order to provide a general overview of the data for subsequent analysis. The descriptive statistics for the main variables are presented in Table 2.

Table 2
Descriptive statistics.

Variables	(1) N	(2) mean	(3) sd	(4) min	(5) max
GGP	31, 525	0.580	0.455	−1.000	1.000
SIZE	31, 525	22.320	1.319	19.310	26.450
LEV	31, 525	0.422	0.201	0.0278	0.934
EM	31, 525	2.069	1.188	1.022	10.790
ROE	31, 525	0.058	0.145	−2.175	0.418
AGE	31, 525	2.943	0.344	1.099	3.689
TOP1	31, 525	0.344	0.151	0.076	0.758
AI	31, 525	1.178	1.275	0.000	4.762
GPR	31, 525	0.292	0.179	−0.070	0.876

Empirical results and analysis

Benchmark regression

Table 3 presents the results of the baseline estimation. Column (1) presents the estimation results with only the core explanatory variables added, column (2) presents the estimation results with other explanatory variables added, column (3) presents the estimation results with only the core explanatory variables added while also controlling for year and industry fixed effects, and column (4) presents the estimation results with other explanatory variables added also controlling for year and industry fixed effects. The coefficient of AI application remains significantly positive, regardless of the inclusion or exclusion of control variables. This indicates that AI application significantly improves green governance performance. The use of AI can promote the green governance performance of listed companies through three key aspects: total asset turnover ratio, price-to-book ratio and cash flow ratio. These three effects interact with each other and jointly promote enterprises' resource investment in the green field.

Robustness check

A series of robustness tests are performed in this study to ensure the precision and reliability of the benchmark regression results:

Table 3
Benchmark regression results.

Variables	(1)	(2)	(3)	(4)
AI	0.017***	0.015***	0.020***	0.011***
	(0.002)	(0.002)	(0.003)	(0.003)
SIZE		0.040***		0.039***
		(0.002)		(0.002)
LEV		0.086***		0.094***
		(0.026)		(0.025)
EM		−0.034***		−0.021***
		(0.004)		(0.004)
AGE		0.036***		−0.012
		(0.008)		(0.009)
TOP1		0.015		0.050***
		(0.018)		(0.018)
GPR		−0.279***		−0.145***
		(0.016)		(0.019)
ROE		0.028		0.034*
		(0.020)		(0.020)
Constant	0.560***	−0.324***	0.557***	−0.235***
	(0.004)	(0.049)	(0.004)	(0.057)
Year fe	No	No	Yes	Yes
Ic fe	No	No	Yes	Yes
Observations	31, 525	31, 525	31, 525	31, 525
R-squared	0.002	0.032	0.094	0.108

Note:*, **, *** are significance levels of 10 %, 5 %, and 1 %, respectively, and values in parentheses are standard errors clustered to the industry-year level, as in the following table.

Exclusion of some samples

To ensure the robustness of the results, observations with extreme values—defined as the top and bottom 1 % of the distribution for each variable—are excluded from the analysis. This procedure mitigates potential bias arising from measurement errors or exceptional circumstances that can distort the regression estimates (Treiblmaier & Filzmoser, 2010). To verify robustness, we exclude the samples in the upper and lower 1 % quartiles of the two variables and re-run the regression analysis for the core explanatory variable, the application of AI, and the explanatory variable, and the governance performance of listed companies (GGP). This treatment can effectively decrease the interference of extreme values on the results and more accurately reflect the regularity characteristics of the sample as a whole. The regression results after removing the extreme values show that the direction and significance of the repercussions of AI applications on the governance performance of listed companies have not changed substantially, regardless of whether the extreme values of the upper and lower 1 % quartiles are included. This finding indicates that the empirical results are both stable and reliable, confirming the robustness of the analysis after controlling for extreme observations. The results are shown in Table 4.

Replacement of explanatory variables

The replacement of the explanatory variables from their original form (GGP) to the logarithmic form ($ln(GGP + 1)$) is intended to mitigate the possible effects of unbalanced data distribution on the regression analysis. By log-transforming the GGP, it is possible to narrow down the data, reduce heteroskedasticity, and ensure that the model is more consistent with classical regression assumptions (Astivia & Zumbo, 2019). The logarithmic transformation also has important economic implications. Improvements in green governance performance generally exhibit diminishing marginal returns, whereby further enhancements require disproportionately greater effort or resource input as governance quality increases. The logarithmic specification captures this non-linear relationship more effectively, making the economic interpretation of the regression coefficients more transparent. As shown by the test results in Table 4, the findings are robust.

Marginal effects analysis

A marginal analysis of the impact of AI-driven applications on green governance performance was conducted, and the results are shown in Fig. 1. This analysis reveals the progressive character of technology application in enhancing performance by refining the trend of green governance performance under different AI application intensities. The performance of the fitted curves shows that the use of AI technology exhibits a continuous positive marginal effect on green governance performance at each marginal change point. The results suggest that, irrespective of the firm's initial level of AI adoption in green governance, performance improves progressively as AI utilization deepens. In the early phase, AI applications primarily target operational efficiencies, such as resource optimization and carbon emission monitoring. With continued integration, AI expands to more advanced domains, including energy management, pollution forecasting, and green technology innovation, thereby enhancing governance performance at higher levels (Ahmad et al., 2021). This finding is consistent with the view that "the growing intensity of AI technology application significantly contributes to the growth of green governance performance."

Table 4
Robustness check results.

Variable	Excluding some sample results GGP	Replacement of explanatory variable results	
		GGP as Dependent Variable	Dependent Variable as ln(GGP + 1)
AI	0.010**(0.004)	0.011***(0.004)	0.008***(0.003)
Constant	0.505***(0.025)	−0.235***(0.089)	−0.174***(0.061)
Observations	31, 115	31, 525	31, 497
R-squared	0.110	0.108	0.116

Based on existing empirical findings, at least within the scope of the sample coverage, no significant diminishing marginal returns have been observed. Instead, a steadily increasing linear pattern emerges. This suggests that in corporate green governance practices, the application of AI technology appears to remain in the "expansion dividend" phase, where each additional unit of application yields substantial governance improvements. The theoretical implication of this trend brings several revelations. First, it indicates that artificial intelligence, as a general-purpose technology, possesses strong scalability and cross-domain applicability. Consequently, the cumulative marginal utility across different governance segments may delay the emergence of diminishing returns. Second, this linear trend does not necessarily imply that the effect will continue indefinitely. Once enterprises reach a certain technological saturation point, as foundational governance areas become fully covered, further AI investments may shift toward areas with lower marginal benefits, gradually revealing diminishing marginal returns.

Endogeneity test

Listed companies are often influenced by their own internal decisions when adopting AI technologies. When choosing whether or not to apply AI, companies may base their decisions on factors such as their existing green governance measures, company culture, and capital status. This selective bias may lead to a tendency for certain companies to adopt AI technologies more aggressively with higher levels of governance, thus affecting the endogeneity of the study (Zaefarian et al., 2017). Since 2017, China's national artificial intelligence strategy and major initiatives have been progressively implemented across multiple industries. Consequently, changes in the average level of AI application within industries are primarily driven by central and provincial policy directives rather than by firm-level strategic choices. Therefore, the growth of artificial intelligence applications can be regarded as an exogenous shock to companies. The adoption of AI is often not completely random, and its distribution may be constrained by a number of factors such as industry characteristics, level of data infrastructure, and external policy changes. This selective process may trigger bias arising from self-selection. In addition, the study in this paper only uses A-share listed companies as the sample and fails to cover SMEs that were not publicly traded, a limitation that may lead to the sample's inadequacy in reflecting the overall characteristics, thus creating the risk of sample selection bias.

To compensate potential selectivity bias, this paper constructs Bartik instrumental variables to solve the possible endogeneity problem (Borusyak et al., 2022). The Bartik instrumental variable AIIV is constructed based on the share-shift method with the following formula (4–1):

$$AIIV_{it} = ai_{it-1} \times \left(aver\_AI_{it} - ave\_AI_{it-1}\right) \tag{4–1}$$

Where $aver\_AI_{it}$ represents the average value of industry-wide AI level of i listed companies in year t.

The outcomes are shown in columns (1) through (2) of Table 5. The first stage regression results present that the estimated coefficient of iv is significantly positive. In addition, the Kleibergen - Paap rk LM statistic has a p-value of "0.0003″ which is significant at the 1 % level, confirming strong correlation between the instrumental and endogenous variables. The Kleibergen - Paap Wald rk F statistic value of 233.79 is greater than the upper limit of 16.38 for the 10 % of weak instrumental variables test, significantly rejecting the original hypothesis that the instrumental variables are invalid (Gulzar & Chaudhry, 2022). The results of the second stage show that after controlling for industry and time fixed effects, the impact of artificial intelligence applications on corporate green governance performance is still significantly positive, that is, the positive impact of artificial intelligence applications on green governance performance is still robust and significant, which enhances the causal

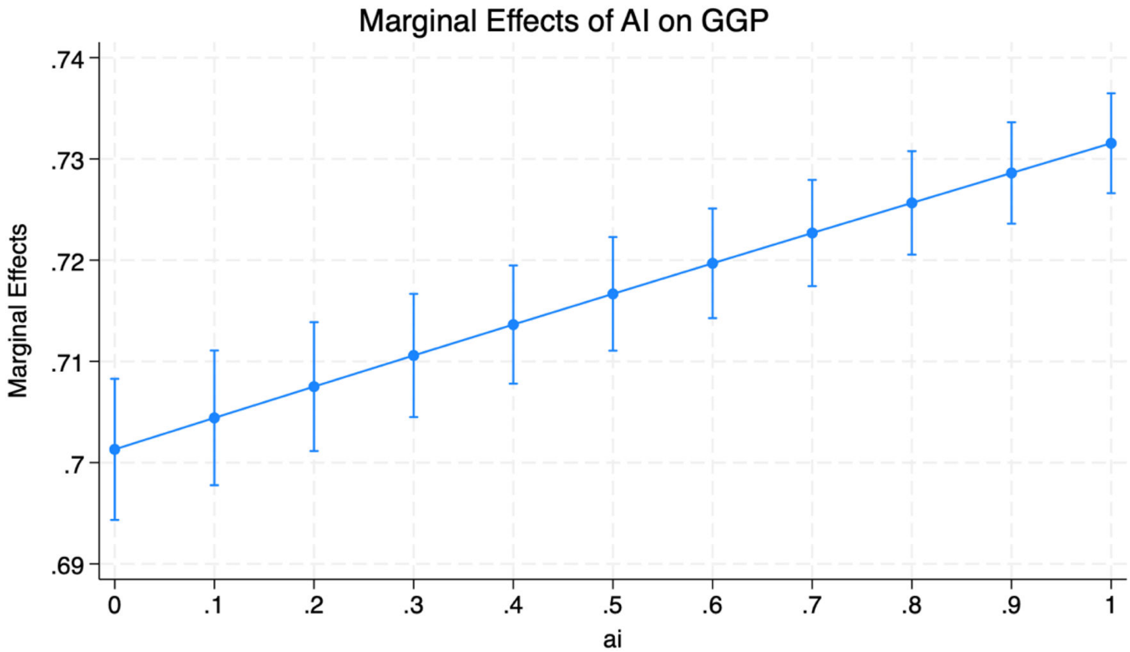

Fig. 1. Marginal effects analysis result.

Table 5
Endogeneity test result.

Variables	Instrumental variables phase I	Instrumental variables phase II
AI		0.040**(0.018)
AIIV	4.703***(0.308)	
Control Variable	Yes	Yes
Year fe	No	Yes
Ic fe	No	Yes
Observations	28, 244	28, 244
R-squared	–	0.017

explanation and reflects the robustness of the core conclusions of this article.

Beyond selection bias and reverse causality issues, other potential sources of endogeneity warrant further scrutiny. First, at the firm level, unobserved organizational characteristics may constitute significant confounding factors. For instance, companies with stronger innovation cultures, higher human capital reserves, or forward-thinking management teams tend to be more proactive in adopting AI technologies while also demonstrating greater responsibility and commitment to green governance. Second, at the industry level, differences in technology diffusion pathways and regulatory constraints across sectors may also act as common drivers. On one hand, high-tech industries possess more robust data infrastructure and R&D networks, making it easier to embed AI into production processes and thereby naturally enhance environmental governance efficiency. On the other hand, resource-intensive or carbon-emission-sensitive industries often face stricter policy regulations and social pressures. In this context, AI adoption is not merely a technological choice but also a strategic response by enterprises to external constraints.

Heterogeneity analysis

Differences in the nature of property rights

State-owned enterprises (SOEs) and non-state-owned enterprises (NSOEs), due to differences in their intrinsic attributes and external environments, have significant differences in government support, policy orientation, access to capital and technological resources, governance structure, decision-making mechanisms, market competition and incentives, and data resource sharing and application. The observed differences in green governance performance, as well as the mechanisms underlying these differences, may vary substantially across ownership types (Zhang et al., 2024). To capture this heterogeneity, the study classifies all listed firms into state-owned and non-state-owned categories. A dummy variable (SOE) is defined to indicate ownership nature, taking the value of 1 for state-owned enterprises and 0 for non-state-owned enterprises. The interaction term between SOE and AI application is incorporated into the baseline regression model to test whether ownership structure moderates the effect of AI adoption on green governance performance. The regression results are shown in Table 6, where the estimated coefficient of AI × SOE is significantly positive, which indicates that the application of AI has a significant property rights nature differentiation characteristics, and the effect on the state-owned nature of the enterprise is stronger. State-owned enterprises typically bear greater social responsibilities, especially in the field of environmental governance. They also receive stronger governmental support and tend to benefit more from policy incentives and preferential allocation of resources. State-owned enterprises have a greater advantage in access to capital and technological resources, especially when AI R&D and applications require high levels of investment, and this difference is particularly significant. In addition, the essence of AI application is centered on the accumulation and processing of data, and state-owned enterprises are more likely to obtain green data

Table 6
Heterogeneity analysis result.

Variables	Nature of property rights	Financing constraints	Environmental Management System Certification
AI × SOE	0.016*** (0.003)		
AI × SA		0.009*** (0.003)	
AI × ISO			0.054***(0.003)
Control Variables	Yes	Yes	Yes
Ic fe	Yes	Yes	Yes
Year fe	Yes	Yes	Yes
Observations	31, 525	31, 525	31, 525
R-squared	0.108	0.108	0.117

resources from the government and industry, and have advantages in data integration and analysis. Therefore, the application of AI has a stronger green governance performance improvement effect on SOEs.

Differences in financing constraints

The financing constraint index (SA) is used as a measure of the degree of financing constraints, and the larger the SA index, the more serious the degree of financing constraints faced by the enterprise. In this paper, the SA index below the 50 % quartile is categorized as the low financing constraint group, and above the 50 % quartile is categorized as the high financing constraint group (Li et al., 2023). A SA index of 1 represents the high financing constraint group, and 0 represents the low financing constraint group. A dummy variable of financing constraints (SA) is constructed, and the interaction term with the application of AI is introduced into the baseline model as the core explanatory variable, and regression is performed. The regression results are presented in Table 6, where the estimated coefficients of AI $\times$ SA are significantly positive, which indicates a significant financing constraint differentiation feature of the use of AI, which exerts a greater impact on the high financing constraint group. High financing constraint enterprises tend to face stronger policy compliance pressure and social responsibility requirements, especially in the context of high-pressure environmental protection policies. This group of enterprises can leverage AI technologies to meet green governance compliance requirements, thereby securing policy-directed financing, tax incentives, or government support that helps alleviate financing constraints. Low-financing constrained enterprises tend to adopt traditional governance tools due to the abundance of capital, and are slower to adopt AI technology. This "path dependence" limits the scope for improving their green governance performance (Lee et al., 2024). In addition, low-financing-constrained firms may invest in multiple areas at the same time (e.g., production automation, marketing, etc.) due to the availability of capital, and relatively insufficient investment in green governance AI technologies, resulting in a fragmented overall effect. Therefore, the application of AI has a stronger green governance performance enhancement effect on high financing constraint firms.

Further analysis reveals that for highly finance-constrained enterprises, AI applications do demonstrate stronger effects in achieving policy compliance and green governance objectives. However, this effect may stem partly from signaling behaviors driven by "external pressure" rather than genuine deep integration. On the one hand, in pursuit of policy-based financing, tax incentives, and government support, firms possibly treat AI technologies merely as a compliance "ticket" rather than as a core strategic driver of green transformation. Such an instrumental approach risks confining AI to symbolic or superficial applications, thereby undermining its potential functional value. On the other hand, the implementation of AI itself entails a range of complex socio-technical challenges. Research by Wang and Zhang (2025) indicates that ethical anxiety can moderate the impact of AI adoption on innovation outcomes. This perspective suggests that even under high financing constraints, AI's positive effects are not unconditionally realized but constrained by the organization's internal psychological and ethical environment. Therefore, future research should further examine the trade-off logic between financial pressure and socio-technical challenges in highly financing-constrained enterprises— specifically, whether companies are using AI technology merely for "window dressing" or driving genuine institutional and capability restructuring.

Environmental management system certification differences

The variable indicating whether a company has passed ISO14001 certification is coded as 1 for certified and 0 for non-certified. A dummy variable for environmental management system certification (ISO) is created, and its interaction with AI application is included as the core explanatory variable in the baseline model for regression analysis. The regression results are shown in Table 6, the estimated coefficient of AI $\times$ ISO is significantly positive, which indicates that there is a significant environmental management system certification differentiation feature of the application of AI, which demonstrates a stronger impact on enterprises that have already passed the ISO14001 certification. Certified enterprises already have a strong foundation in green governance practices, and the application of AI technology can further optimize their existing environmental management processes (Treacy et al., 2019). In the case of non-certified enterprises, incomplete management structures and weak institutional mechanisms hinder the effective deployment and integration of AI technologies, resulting in only limited improvements in green governance performance. Therefore, the application of AI has a stronger enhancement effect on ISO14001-certified enterprises.

Analysis of impact mechanisms

This research refers to the investigation of Jiang (2022) to verify the causal mediation effect for testing. The model is constructed as follows:

$$M_{it} = \beta_0 + \beta_1 AI_{it} + X_{it}\gamma + \sigma_j + \sigma_t + \varepsilon_{it} \tag{4–2}$$

Where i denotes the listed company; t denotes the year; σ_i is the industry fixed effect; σ_j is the year fixed effect; ε_{it} is the error term; and M is the mechanism variable.

Total asset turnover rate improvement effect

The mechanism of the impact of the application of AI on the green governance performance of listed companies is explored from the perspective of the improvement of the company's operational efficiency, which cuts into the impact of the application of AI on the total asset turnover ratio. The total asset turnover ratio is regarded as a comprehensive symbol that reflects the balance between a firm's operational efficiency and governance costs (He et al., 2021). The total asset turnover ratio is a measure of a firm's ability to utilize its assets to generate revenue, with higher values indicating stronger asset utilization efficiency, i.e., lower values of management costs and supervision costs indicate higher internal governance efficiency. In the context of green governance, this indicator mediates the effect of AI on operational efficiency and governance cost optimization, ultimately enhancing green governance performance. It indicates how firms balance the relationship between operational efficiency and governance costs in pursuing green goals. Table 7 displays the outcomes of the mechanism analysis.

From the results, it is noticeable that the application of AI significantly improves total asset turnover ratio. This corporate performance metric can be improved in three ways: first, optimizing resource allocation. AI technology can improve the enterprise's resource utilization efficiency (e.g., logistics, inventory management, etc.) through accurate prediction and data analysis, thus improving the asset turnover ratio; second, improving the business process. Intelligent production, supply chain optimization, etc. can reduce waste and enhance the asset operation efficiency of enterprises. Third, expanding new business. The application of AI can create new sources of income for enterprises, such as green product research and development, carbon emission reduction

Table 7
Results of the analysis of impact mechanisms.

Variables	Total asset turnover rate	P/B ratio	Cash flow ratio
AI	0.020***(0.002)	0.040**(0.016)	−0.002***(0.000)
Control Variables	Yes	Yes	Yes
Ic fe	Yes	Yes	Yes
Year fe	Yes	Yes	Yes
Constant	0.834***(0.046)	22.290***(0.421)	−0.169***(0.008)
Observations	31, 525	31, 525	31, 525
R-squared	0.380	0.349	0.170

related services, and so on.

The strong correlation between total asset turnover and green governance performance can be summarized as follows: 1. AI reduces the agency cost and improves the total asset turnover; 2. The improvement of total asset turnover provides support for the optimization of green governance resources, technological innovation, and stakeholder coordination; 3. The optimization of green governance resources and capabilities directly enhances green governance performance. We describe these in formula (4–3):

$$Y_g = \gamma_0 + \gamma_1 TAT + \varepsilon \tag{4–3}$$

Where Y_g is the green governance performance; TAT is the Total asset turnover; γ_0 is the intercept term, which indicates the baseline level of green governance performance when the TAT is zero; γ_1 is the impact coefficient of the TAT, which captures the marginal contribution of each unit increase in the total asset turnover to the green governance performance; and ε is the stochastic error term, which captures the unexplained other impact factors.

P/B ratio enhancement effect

The price-to-book ratio (P/B Ratio) is an important financial indicator that reflects the market value of listed companies relative to their book value. It not only reflects the capital market's forecast of the company's future profitability and growth prospects, but also indirectly reflects the company's performance in green governance, sustainable development, and other aspects (Nezlobin et al., 2016). Within the framework of green governance, this indicator functions as a mediating variable that transmits the impact of AI technology—via improvements in firms' price-to-book ratios—into enhanced green governance performance. Table 7 shows the results of the mechanism analysis.

As can be seen from the results, the application of AI has significantly improved the price-to-book ratio. A higher price-to-book ratio indicates strong market expectations for the company's future growth, reflecting its effective resource allocation and innovation capabilities. AI application exerts both direct and indirect effects on market value and net assets through various paths, thereby changing the price-to-book ratio level. The following is an analysis of the specific transmission mechanism. First, the application of AI improves operating efficiency and profitability: The implementation of AI in production, supply chain operations, customer service and other fields has significantly reduced operating costs through automation and intelligent processes. In addition, through AI-driven precision marketing, customer behavior prediction and new product development, companies can more effectively gain market share and increase revenue; second, AI applications reduce intangible asset impairment: AI technology can help companies develop and protect intellectual property more efficiently, thereby reducing the risk of intangible asset impairment and further enhancing the robustness of net assets (Moro-Visconti, 2024). Changes in the price-to-book ratio not only reflect the capital market's recognition of the value of AI technology, but also drive companies to further increase their investment in technology and form a positive cycle.

For the mechanism of the price-to-book ratio on the transmission path of green governance performance, there are the following explanations: First, the impact of the price-to-book ratio on resource availability: Companies with high price-to-book ratios usually have stronger capital market financing capabilities and can obtain sufficient funds through equity financing or debt financing. These resources provide basic support for the implementation of green governance projects, such as investing in green technology research and development and promoting green supply chain transformation. In addition, a higher price-to-book ratio may alleviate financial constraints by improving firms' balance-sheet strength and debt-servicing capacity. Consequently, such firms are better positioned to undertake the substantial investment required for green transformation. Second, the price-to-book ratio reflects green market expectations: investors are showing growing concern over the performance of companies in terms of environment, social responsibility and governance (ESG). Companies with high price-to-book ratios may gain more recognition from investors through their excellent green governance strategies, thereby attracting long-term capital (Mooneeapen et al., 2022). This constitutes a positive feedback mechanism. Companies with high price-to-book ratios tend to continue to attract green investment funds, which conversely enhances the company's ability to invest in green governance resources, forming a positive cycle.

Cash flow ratio reduction effect

The cash flow ratio reflects the short-term debt repayment ability of an enterprise (Yazdanfar & Öhman, 2015). In the context of the application of AI, the cash flow ratio is affected by the technological upgrading and resource allocation changes of the enterprise, especially in the field of green governance. This impact may be manifested as a reduction in the ratio, but it may eventually drive the enhancement of green governance performance. Table 7 shows the results of the mechanism analysis.

As indicated by our findings, the application of AI exerts a significant negative effect on the cash flow ratio. Accordingly, we conduct a rigorous examination of the mechanisms and transmission channels through which this reduction affects green governance performance. Regarding the mechanism of the reduction of the cash flow ratio by the application of AI, first: increased capital expenditure (Capex) leads to a decrease in cash flow. The application of AI requires substantial early-stage financial commitment, including algorithm development, equipment procurement and system upgrades. These expenditures significantly consume the cash flow from operating activities of the enterprise (Moro-Visconti, 2024). The introduction of AI is usually accompanied by high research and development investment (R&D), which cannot be directly converted into operating cash flow in the short term, resulting in a decrease in the cash flow ratio. Second: Expansionary strategies lead to an increase in current liabilities. In order to support technological upgrades and green governance projects related to AI, enterprises may increase current liabilities through debt financing. The application of AI promotes business expansion, but is accompanied by higher short-term current liabilities, such as prepaid expenses in supply chain adjustments or project working capital requirements. In addition, AI plays a crucial role in enhancing the long-term performance of enterprises, but the full benefits have not been shown in the short term, and the initial impact has led to insufficient cash flow from short-term operating activities. Regarding the transmission mechanism of cash flow ratio on green governance performance, first: changes in green investment intensity caused by the reduction of cash flow ratio. Despite the reduction of cash flow ratio, enterprises prioritize resources to green governance projects with high strategic value, reflecting the synergy between AI and green strategy. AI improves the efficiency of capital use, enabling enterprises to achieve green governance goals with less cash flow, thereby alleviating the negative effects of the reduction of cash flow ratio. Despite the reduction in cash flow, green governance performance is still improving. Second: the role of reduced cash flow ratio in promoting resource integration and synergy. The application of AI makes it easier to attract external green capital support by improving the technical capabilities and green governance reputation of enterprises. For example, enterprises can make up for the lack of cash flow with the help of green bonds, government subsidies, etc. (Maltais & Nykvist, 2020). Third: Long-term sustainability perspective: enhanced feedback of green performance. The reduction of cash flow ratio may be the result of strategic investment by enterprises in the green field. This investment ultimately enhances green governance performance by increasing resource utilization efficiency and reducing pollution emissions. Although strategic investments in green governance may temporarily lower the company's cash flow ratio, they can simultaneously strengthen its market reputation and capital market valuation, thereby generating a positive feedback loop.

The adoption of artificial intelligence applications does indeed lead to a decline in cash flow ratios through mechanisms such as increased capital expenditures and expanded current liabilities. However, this contraction in short-term liquidity is not merely a financial issue but reflects complex tensions with corporate green governance pathways. While the decline in cash flow ratios partially translates into enhanced green governance performance through prioritized resource allocation and efficiency gains, this “liquidity-for-green-strategy” model may conceal long-term risks. AI adoption typically involves intensive R&D and fixed-asset investments. While such expenditures weaken short-term liquidity, they lay the groundwork for future green governance performance through technological advancement and efficiency gains. The “temporary tightening” of cash flow is an inevitable consequence of enterprises proactively pursuing strategic transformation and green innovation. From a long-term development perspective, liquidity pressures are unavoidable. However, the long-term reputational capital and market recognition gained by enterprises often generate a “positive feedback loop” in subsequent stages, offsetting or even surpassing earlier liquidity losses. It can be argued that a “structural tension” exists between the positive effects of AI applications on green governance and the potential risks stemming from declining cash flow. This tension indicates that enhanced green governance performance does not necessarily guarantee robust financial sustainability. Future research could further investigate this inherent tension by exploring how firms balance short-term liquidity pressures with long-term green innovation objectives across different institutional contexts, financing conditions, and policy frameworks. This will foster a more comprehensive understanding of the complexities involved in strategic investments in sustainable technologies. Therefore, this mechanism suggests that a decline in the cash flow ratio should not be interpreted as a negative signal, but as a deliberate strategic decision by firms pursuing technological upgrading and green transformation—one that embodies long-term value creation and sustainable development objectives.

Discussion

AI enhances green governance as part of a broader system driving green innovation. Governance gains—better data, resource use, and compliance—serve as foundations for outcomes like green products and sustainable models. Echoing the insights of Wang and Zhang (2025), this study conceptualizes AI-driven governance not only as a mechanism for systemic enhancement but also as a strategic lever that propels firms beyond sustainability toward transformative innovation and enhanced ecosystem resilience. This paper focuses on AI’s role in enterprise green governance, yet such effects extend across supply chains and industry networks. Partner capacity and collaboration can amplify or weaken AI’s impact. Research shows cross-organizational collaboration strengthens digital green supply chains’ ecological innovation (Wang et al., 2024). Future studies should examine how AI drives collaboration through information sharing, resource coordination, and joint emissions reduction, enabling systemic sustainable value creation.AI enhances green governance by improving asset turnover, price-to-book ratio, and cash flow, aligning with resource-based theory that stresses effective use of resources. It also reflects dynamic capabilities theory, as AI enables firms to adapt through data analysis and monitoring. Thus, AI optimizes efficiency, drives strategic transformation, and promotes sustainable green development.

Conclusions and policy recommendations

Conclusions

At present, AI technology is swiftly advancing across diverse industries, gradually establishing itself as the "digital cornerstone" that is shaping and driving the future of economic and social development. Combining AI with green governance has become an inevitable path to achieve sustainable development goals. The continuous breakthroughs in AI technology have become a powerful engine to promote corporate green governance. Drawing on the findings of this study’s empirical analysis, AI applications can significantly improve the green governance performance of listed companies. Companies can use the powerful data mining and analysis capabilities of AI to more deeply identify and track their impact on the environment. This conclusion offers a fresh viewpoint and basis for related theoretical research and practical exploration.

Policy recommendations

Based on the findings of this empirical study, the following recommendations are proposed: First, policy orientation should focus on enhancing total asset turnover efficiency. Policymakers should encourage enterprises to leverage artificial intelligence to optimize production processes, thereby improving the utilization efficiency of green assets. Governments can implement policies to promote the application of AI technologies in energy management systems, increase the proportion of renewable energy usage, and reduce energy waste during production. Simultaneously, dedicated funds should be established to support AI applications in smart manufacturing, low-carbon production, and green supply chain management, thereby accelerating the green transformation of corporate assets. It is crucial to emphasize that, given empirical evidence indicating state-owned enterprises demonstrate more pronounced green governance outcomes through AI adoption, policies should prioritize positioning SOEs as industry benchmarks for “AI + green governance.” Leveraging their exemplary role can catalyze green transformation across the entire sector. Second, regulatory recommendations based on the price-to-book ratio enhancement effect. Regulatory authorities should enhance the standardization of environmental information disclosure by requiring listed companies to adopt AI technologies that improve the accuracy, completeness, and traceability of environmental data. Concurrently, financial institutions should be encouraged to incorporate enterprises’ AI-driven green governance capabilities into investment decisions, thereby amplifying the influence of ESG ratings on capital market valuations and fostering a virtuous cycle of green value enhancement. Considering varying financing constraints across enterprises, policy support for SMEs and private firms facing greater funding pressures should extend beyond low-interest loans. Establishing technology support centers or industry-academia-research collaboration platforms would provide these entities with AI application guidance and talent training, ensuring capital drives substantive green governance improvements rather than superficial technology adoption. Third, deepen the integration of green finance and artificial intelligence. Governments should guide financial institutions to offer differentiated financial support to enterprises leveraging AI for green governance, such as establishing dedicated “AI + Green Governance” credit lines and green bond policies to provide low-interest loans and diversified financing channels. Concurrently, governments and financial institutions can strengthen funding support for green AI projects, fostering a multi-tiered green finance support system. Furthermore, regulators can encourage enterprises to leverage AI for optimized financial management, rationally allocate green investment budgets, and ensure liquidity aligns with green governance expenditures. This approach prevents short-term financial pressures from constraining enterprises’ long-term green transformation.

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Declaration of competing interest

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