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The impact of artificial intelligence on corporate green innovation: Can "increasing quantity" and "improving quality" go hand in hand?

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Abstract: In the current era of digitalization and greenization, it is of great importance to explore how enterprises utilize artificial intelligence (AI) to promote green innovation. This paper explores the green innovation effects of AI and its underlying mechanisms from the perspective of corporate governance, using a sample of Chinese A-share listed companies from 2007 to 2021. Our results show that AI has a significant positive impact on corporate green innovation, in terms of both quantity and quality. We investigate the mechanisms behind and find that AI enhances corporate green innovation through channels of increasing human capital accumulation, enhancing organizational management efficiency, and improving the quality of environmental information disclosure. Further, we find that the effects of AI on green innovation are particularly pronounced for state-owned enterprises and large enterprises. In policy pilot zones, AI significantly increases the quantity of corporate green innovation while the impact of AI on the quality of corporate green innovation is not significant. Moreover, we find that AI exerts a diffusion effect rather than a crowding-out effect on enterprises' other innovative activities, and AI enhances corporate green innovation resilience. These results contribute to the academic literature and policy debate on the importance of AI to promote corporate green innovation.

Keywords: Artificial intelligence; Corporate green innovation; Quantity and quality; Diffusion effect; Crowding-out effect; Green innovation resilience

1. Introduction

Green innovation, with its economic, environmental and social benefits, has become an important means to address climate change and to achieve sustainable development. Enterprises, as the leading innovator and the primary polluters, their green innovation capacity not only determines their own competitiveness, but also impacts the achievement of countries' commitment to Paris Agreement (Sun et al., 2023a, 2023b). In recent years, artificial intelligence (AI) has increasingly emerged as a crucial driver for global industrial transformation and social progress, with the new era of technological revolution characterized by digitalization. While the traditional development pattern often fails to balance economic growth and the environment, recent studies show that AI contributes to both economic development and environmental protection (Ghobakhloo and Fathi, 2021). Due to its merits in processing information, analyzing complex data and optimizing production processes, AI has been increasingly utilized by enterprises in green innovation (Shahzad et al., 2022). Therefore, whether AI can effectively promote corporate green innovation, and if so, what are the underlying mechanisms? What policies should be implemented to utilize the effect of AI on green innovation? These questions are of great importance for economic growth and green strategies of countries worldwide.

The impact of AI on economic and social development has become a topical issue in recent years. Many studies examine the impact of AI on corporate performance and labor markets. Some argue that the adoption of AI technology significantly optimizes resource allocation, thus improving corporate performance (Wamba-Taguimdje et al., 2020). While some warn that AI may lead to "productivity paradox" (Acemoglu and Restrepo, 2018). For AI and firm labor structure, existing studies conclude that AI leads to an increase in the share of high-skilled labor (Xie et al., 2021). At the macro level, the existing literature has explored how AI affects economic growth, industrial transformation, employment and income. Some studies show that AI improves the efficiency of the economic system (Murphy, 2024), drives

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intersectoral production factor mobility thus resulting in changes to industrial structure (Acemoglu and Restrepo, 2019), and generates new employment opportunities (Wang et al., 2024b). However, the literature also indicates that AI exerts a substitution effect on low-skilled jobs, thereby exacerbating income gap between high- and low-skilled labor (Cornelli et al., 2023).

The role of AI on corporate green innovation has not received its deserved attention. The existing literature exploring the determinants of corporate green innovation mainly focuses on the roles of environmental regulation (Rubashkina et al., 2015; Zhang et al., 2020; Zhou et al., 2023), economic policies (Tian et al., 2021; Wang and Wang, 2021; Sun et al., 2024a), and market incentives (Chadha, 2011; Olson, 2013), while the research on the role of AI is still limited. Some studies suggest that the technological benefits of AI significantly improve the production framework of enterprises and promote the incorporation of green technologies into the production processes (Wang et al., 2024a). This integration leads to a reduction in pollution emissions and enhances environmental sustainability of enterprises (Zhou et al., 2024). Regarding green innovation, some suggest that AI facilitates risk management in production and improves resource allocation efficiency for green R&D (Liang et al., 2024). However, some studies indicate that the influence of AI on green innovation is not universally beneficial (Cheng et al., 2024). Once AI reaches a certain threshold, enterprises may become overly dependent on it, which could hinder sustainable advancements in green innovation (Wang et al., 2023).

The question of whether AI has a green innovation effect, along with the underlying mechanisms, is still under exploration. Among the limited literature addressing the relationship between AI and green innovation, most studies analyze the mechanisms from the production and distribution perspectives, while the influence of internal corporate governance is overlooked (Wang et al., 2024b). Given that the effectiveness of internal corporate governance is the fundamental factor determining the green innovation capability of enterprises, this study analyzes the mechanisms of AI affecting corporate green innovation based on the perspective of internal corporate governance. In addition, we investigate whether AI influences firms' other innovation activities while fostering corporate green innovation, and the resilience of AI on green innovation, which have been ignored in the literature.

We contribute to the existing literature in the following ways. First, we investigate the impact of AI on corporate green innovation and look at both the quality and quantity of enterprises' innovation. We analyze the mechanisms of AI-induced corporate green innovation from the perspective of internal corporate governance. To this end, we incorporate enterprises' human capital, organizational management, and environmental information disclosure as channels into the theoretical framework of AI and green innovation¹.

Second, we explore how AI-induced green innovation affects enterprises' other innovative activities. Under the constraints of environmental regulations, enterprises usually allocate their limited resources to green R&D, which results in a crowding-out effect on other innovative activities. However, green innovation also relies on enterprises' overall innovation capabilities and the development of green innovation further enhances enterprises' innovation level (Hao et al., 2022), which generates a positive diffusion effect on enterprises' other innovative activities. Therefore, we further examine whether this AI-induced green innovation exerts a "crowding out" effect or a "diffusion" effect on enterprises' other innovative activities.

Third, we discuss whether AI enhances corporate green innovation resilience. The existing studies mainly focus on the relationship between AI and business resilience (Schintler and McNeely, 2022), while whether AI affecting corporate green innovation resilience has largely been ignored. This question is of great importance as green innovation resilience reflects enterprises' ability to withstand environmental challenges and demonstrates their durability and stability in promoting green innovation.

The rest of this paper is organized as follows. Section 2 discusses the mechanisms through which AI fostering green innovation and proposes the corresponding hypotheses. Section 3 introduces the data and empirical framework. Section 4 presents the empirical results. Section 5 the mechanism analysis. Section 6 conducts the heterogeneity analysis. Section 7 the further analysis, and the conclusions are set out in Section 8.

¹ Financing constraints faced by enterprises and executives' cognition of green transition also affect business decisions and internal governance, which are frequently identified as channels influencing corporate green transition in some studies (Wong et al., 2011; Bettarelli, 2024). The analysis and tests for these two micro-mechanisms are provided in Appendix A.

2. Theoretical analysis and hypotheses development

2.1. AI and corporate green innovation

As a significant advancement in scientific and technological development, AI plays an increasingly important role in enhancing enterprises' productivity and environmental governance. It serves as a key catalyst for corporate green innovation (Sun et al., 2024b). The positive effects of AI on corporate green innovation can be observed in three aspects: improving workers' green literacy, enabling intelligent environmental monitoring and response, and promoting automated and intelligent production. First, the integration of AI can streamline repetitive tasks in enterprise operations, leading to a transformation in the labor structure from skill-oriented to knowledge-oriented. This shift requires and improves skill levels among employees, which in turn drives the adoption and dissemination of green technologies, resulting in green technology spillover effects (Tschang and Almirall, 2021). Consequently, this fosters the development of green innovation networks within enterprises and increases the overall level of green innovation (Li, 2022). Second, AI can effectively monitor enterprise environmental behaviors in real-time through sensors and data analysis, facilitating the identification of sources of environmental pollution and energy waste. This capability lays the groundwork for research on green technologies and products, optimization of production processes, and establishment of environmental management systems within enterprises (Zhang et al., 2021). Finally, automated and intelligent production represents a primary avenue for enterprises to achieve green innovation. The adoption of AI technologies in industrial robots and related equipment enhances the autonomy and intelligence of production processes. This leads to improvement in productivity and efficiency in resource utilization, and enables precise and intelligent control of pollutant emissions, thereby driving green innovation (Rammer et al., 2022).

Based on the above analysis, we propose our **hypothesis H1**: *AI facilitates corporate green innovation*.

2.2. Micro-mechanisms of AI-induced corporate green innovation from a corporate governance perspective

Efficient internal governance ensures the transparency of enterprises in the process of decision making, implementation and supervision, and provides a stable institutional environment and an effective incentive and constraint mechanism for enterprises to conduct green innovation. We analyze the mechanisms of how AI promotes corporate green innovation from the channels of human capital, organizational management, and information disclosure. The basic theoretical mechanisms are illustrated in Fig. 1.

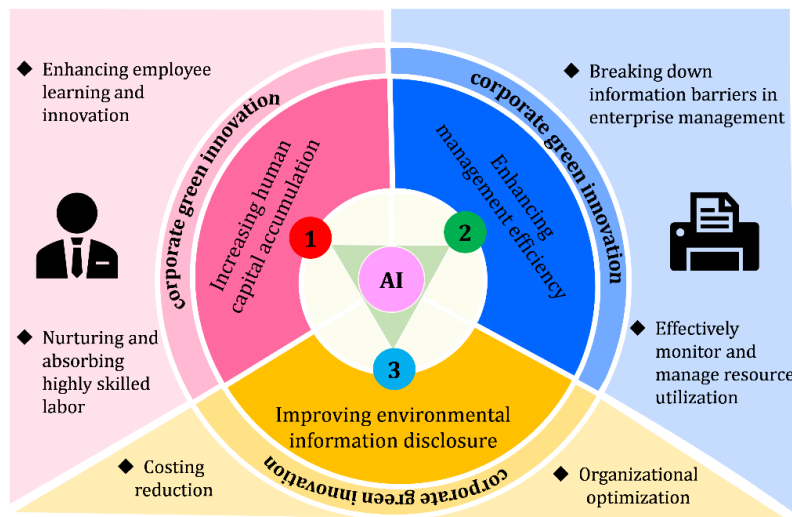


Fig. 1. Diagram of micro-mechanisms by which AI affects corporate green innovation

Firstly, AI promotes corporate green innovation by increasing human capital. Human capital plays a crucial role in enabling enterprises to engage in green innovation. With skilled workforce and professional talents, enterprises can effectively respond to environmental regulations and market demands, develop sustainable products, and enhance their

capacity for green innovation (Raza and Khan, 2022). The advancement and adoption of AI technologies have expanded opportunities for employees to access education and training, allowing them to enhance their environmental literacy and enabling enterprises to quickly integrate cutting-edge green knowledge and technologies. This, in turn, accelerates human capital accumulation within enterprises (Ramachandran et al., 2022). Furthermore, there is a pressing demand for well-educated labor in areas such as machine learning, big data analysis, and algorithm design within the realm of AI, which further contributes to the accumulation of human capital within enterprises (Gofman and Jin, 2024).

Secondly, AI promotes corporate green innovation by improving management efficiency. An enterprise's governance capability is closely tied to the effectiveness of its management organization and operational mode (Naciti et al., 2022). Enhanced management efficiency enables enterprises to closely monitor resource utilization, upgrade traditional production processes and manufacturing technologies to address environmental challenges, thereby preventing resource wastage and pollution emissions resulting from inefficient production approaches. While conventional management approaches often rely on manual processes, leading to information silos between different departments within the enterprise. This hinders information sharing and communication, affecting management efficiency (Varadaraj and Wadi, 2021). The emergence of AI not only automates repetitive tasks and breaks down information barriers but also aids enterprises in making more precise market forecasts, demand predictions, and risk assessments through data mining technologies, ultimately enhancing corporate management efficiency (Papagiannidis et al., 2023).

Thirdly, AI promotes corporate green innovation by improving the quality of corporate environmental information disclosure. By providing high-quality environmental information, enterprises can convey positive signals regarding their green development to the market, which encourages investors to offer resource support for their green innovation activities. Furthermore, through the disclosure of environmental information, enterprises can better identify their shortcomings in energy conservation and environmental protection, thereby stimulating the momentum for green innovation (Effah et al., 2023). AI improves the quality of corporate environmental information disclosure primarily through two ways. On the one hand, the application of AI automates various operational processes within enterprises, leading to reduced production costs and thereby increasing the capital investment available for environmental information disclosure (Mithas et al., 2022). On the other hand, AI enhances the transparency and timeliness of information dissemination, thereby mitigating the potential for corporate deception in the environmental information disclosure (Robinson, 2020).

Based on the above analysis, we put forward the **hypothesis H2**: *AI promotes corporate green innovation through channels of increasing human capital, enhancing management efficiency, and improving the quality of environmental information disclosure.*

3. Methodology

3.1. The empirical model

We establish the following econometric model to examine the effect of AI on corporate green innovation:

$$Y_{it} = \alpha_0 + \alpha_1 AI_{it} + \sum \alpha_j CV_{j,it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

where i and t denote enterprise and year, respectively. Y refers to corporate green innovation and represents two measures: the quantity of corporate green innovation (labeled *griquan*) and the quality of corporate green innovation (labeled *griqual*). AI refers to the AI development level of enterprises. CVs represent a series of control variables that affect corporate green innovation. μ , λ , and ε represent individual fixed effects, time fixed effects, and random disturbance terms, respectively.

According to our theoretical analysis, AI may facilitate corporate green innovation by increasing human capital, enhancing management efficiency, and improving the quality of environmental information disclosure. Based on Akerman et al. (2022), we extend Eq. (1) and construct the following econometric model to examine these channels:

$$Y_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 M_{it} + \beta_3 AI_{it} \times M_{it} + \sum \beta_j CV_{j,it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

where M refers to the mechanism variable, including three measures, namely, the level of human capital accumulation, corporate management efficiency, and the quality of environmental information disclosure.

3.2. The measurements

3.2.1. The dependent variable

There are several approaches to measure green innovation in the literature. One method is to construct a comprehensive evaluation index based on input-output theory, which is commonly used in macro-level empirical research. In micro-level studies, green patents are frequently employed as a measure for green innovation. Given green patents directly reflect the actual impact of corporate green innovation, we use green patents to measure corporate green innovation. Specifically, following [Li and Xiao \(2020\)](#), we define the quantity of corporate green innovation (*griquan*) as the natural logarithm of the number of green patent applications submitted by listed companies plus one. To assess the quality of corporate green innovation (*griqual*), we use the natural logarithm of the number of citations of green patents filed by listed companies plus one. The citations reflect a patent's technological influence and market value. Patents with high citations indicate that their technologies are widely accepted and utilized by subsequent innovations, suggesting their substantial contributions to the technological advancement of related fields ([Kim and Valentine, 2021](#)). Furthermore, citations serve as an indirect measure of a technology's popularity and its cross-industry impact, which is essential for evaluating the practical application of an innovation. Compared to the number of green patents, citations can effectively differentiate between high-quality and low-quality green innovations ([Aghion et al., 2013](#)).

3.2.2. The independent variable

Industrial robots play a crucial role in enterprises' intelligence development. Based on the stock of industrial robots, the literature develops the "robot penetration" indicator as a proxy for enterprises' level of AI ([Acemoglu and Restrepo, 2020](#)). Given that AI, being a digital technology, is technical in nature, we take natural logarithms of the number of AI patents filed by listed companies plus one to measure the level of AI development in enterprises. This measure reflects the utilization of AI technologies in enterprise development over time and space and demonstrates the AI technologies already possessed by enterprises, and further reveals the output status of enterprise AI technologies ([Yao et al., 2024](#)).

3.2.3. Mechanism variables

Our first mechanism variable is human capital accumulation (*hcl*). Following [Caloghirou et al. \(2022\)](#), we measure the level of corporate human capital accumulation as the share of R&D personnel in the total number of employees. R&D personnel are often associated with high levels of knowledge, skills, and innovation, making them a suitable proxy for corporate human capital. The second mechanism variable is corporate management efficiency (*mef*). We measure it as the ratio of the sum of administrative expenses and selling expenses to total operating income, following [Chen et al. \(2020\)](#). The third mechanism variable is the quality of corporate environmental information disclosure (*eid*). Following [Kong et al. \(2024\)](#), we quantify it in terms of environmental management, environmental certification, disclosure carriers, environmental liabilities, environmental performance and governance disclosure.

3.2.4. Control variables

To mitigate the estimation bias caused by omitted variables, we include the following control variables in our regressions following the existing studies ([Gan et al., 2023](#); [Bai et al., 2025](#)):

- The size of the enterprise (*scale*), measured by the logarithm of the enterprise's total assets.
- Debt to asset ratio (*doar*), calculated as the ratio of the enterprise's year-end total liabilities to its total assets.
- Capital intensity (*kir*), represented by the logarithm of the enterprise's fixed assets divided by its number of employees.
- Shareholding concentration (*shr*), measured by the proportion of shares held by the largest shareholder.
- The level of cash flow (*cfo*), measured by the ratio of net cash flow from operating activities to total assets.
- Enterprise growth (*grw*), expressed as the growth rate of operating income.
- Profitability (*roa*), expressed as the ratio of net profit to total assets.
- Independence of directorate (*indep*), measured by the proportion of the number of independent directors to the total number of directorates.
- Current ratio(*liquid*), equal to the ratio of current assets to current liabilities.

- Fixed asset ratio(*fixasset*), is the ratio of net fixed assets to total assets.

3.3. Data sources

This study investigates the effects and mechanisms of AI on corporate green innovation using a comprehensive panel data of Chinese A-share listed companies in Shanghai and Shenzhen from 2007 to 2021². We exclude enterprises with significant missing data and those were delisted or at risk of delisting (ST, *ST). The data of enterprises' green patent is obtained from Chinese Research Data Service Platform (CNRDS). The corporate AI patent data is sourced from China National Intellectual Property Administration (NIPA). The basic information and financial data of enterprises are from China Stock Market & Accounting Research Database (CSMAR). The regional data are from China City Statistical Yearbook and statistical yearbooks of provinces and cities. Table 1 reports the descriptive statistics of our variables.

Table 1

Descriptive statistics of variables

Variable	Obs.	Mean	S.D.	Min.	Max.
<i>griquan</i>	13734	0.5176	0.9504	0.0000	6.8057
<i>griqual</i>	13734	0.7603	1.0986	0.0000	7.0570
<i>AI</i>	13734	2.6994	1.6004	0.6931	10.1484
<i>hcl</i>	10082	17.8239	14.4814	0.0000	93.6700
<i>mef</i>	13734	0.0859	0.1048	-0.1108	7.2843
<i>eid</i>	13666	2.1446	0.9537	0.0000	3.8918
<i>scale</i>	13734	22.6915	1.4035	18.3492	28.6364
<i>doar</i>	13734	0.4632	0.1943	0.0110	0.9967
<i>kir</i>	13734	12.6521	1.1724	4.8349	19.5780
<i>shr</i>	13734	33.7627	15.5347	0.2900	89.9900
<i>cfo</i>	13734	0.0481	0.0682	-0.6498	0.5327
<i>grw</i>	13734	0.2658	4.2569	-0.9713	429.0361
<i>roa</i>	13734	0.0357	0.0744	-1.1296	0.6754
<i>indep</i>	13734	37.6544	5.7242	16.6700	80.0000
<i>liquid</i>	13734	2.0480	2.5359	0.0794	144.0000
<i>fixasset</i>	13734	0.2114	0.1616	0.0002	0.8758

4. Empirical Results

4.1. The benchmark regressions

We start by analyzing the effects of AI on corporate green innovation using Eq. (1). The results are reported in Table 2. The control variables are excluded from columns (1) and (2), while columns (3) and (4) include these variables. Columns (1) and (3) illustrate the impact of AI on the quantity of corporate green innovation, and columns (2) and (4) are for the quality of corporate green innovation. The results show that the coefficients of *AI* on both quantity (*griquan*) and quality (*griqual*) are significantly positive at the 1% level, regardless of the inclusion of control variables. This indicates that AI not only enhances the quantity of corporate green innovation, but also promotes its quality, leading to a coexistence of "increasing quantity" and "improving quality" effects. Specifically, a 1% increase in the level of enterprises' AI is associated with a 0.35% increase in the quantity and a 0.08% enhancement in the quality of their green innovation, thereby supporting hypothesis H1. Besides, the coefficient of *AI* on quantity (*griquan*) exceeds that of quality (*griqual*), indicating that the "increasing quantity" effect of AI on corporate green innovation is stronger than the "improving quality" effect.

² Our sample starts from 2007 for the following reasons. First, the onset of the third peak in AI development occurs in 2006 with the introduction of deep learning model by Jeffrey Hinton and others facilitated by the rapid advancement of Internet information technologies. Thus, we use 2007 as the starting point for this study to reflect the characteristics of AI development progress. Second, our measure for enterprises' AI level is based on AI patent applications. According to the China Artificial Intelligence Industry Market Outlook Research Report 2019, the patent statistics for AI in China was gradually refined since 2007, thereby ensuring our data quality.

This is because green innovation is quantitatively captured by the growth in the volume of green patent applications, reflecting both the activity degree and output scale. In terms of quality, green innovation focuses on technological breakthroughs, application scenarios and market competitiveness, which require time for testing. This leads to a relatively modest improvement effect of AI on the quality of corporate green innovation. In addition, quality enhancement typically depends on the accumulation of quantity; only when the degree and scale of enterprises in green innovation reach a certain threshold can they achieve more technological breakthroughs, broader application prospects, and greater market value.

Table 2

Benchmark regression results

Variables	(1)	(2)	(3)	(4)
	<i>griquan</i>	<i>griqual</i>	<i>griquan</i>	<i>griqual</i>
<i>AI</i>	0.3467*** (0.0209)	0.0960*** (0.0175)	0.3453*** (0.0208)	0.0818*** (0.0167)
<i>_cons</i>	0.5849*** (0.0108)	2.6774*** (0.0090)	-0.2062 (0.6111)	-3.4996*** (0.9653)
<i>CVs</i>	NO	NO	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
<i>R</i> ²	0.7601	0.9032	0.7604	0.9091
<i>N</i>	13477	13477	13477	13477

Note: (i) Robust standard errors clustered to the firm-level are in parentheses. (ii) *, **, and *** denote significant at the 10%, 5%, and 1% levels, respectively. (iii) When using the `reghdfe` command for fixed effects estimation, singleton observations are automatically excluded, coupled with the presence of missing values for some variables, leading to different sample observations in empirical tables compared to Table 1. Same below if not otherwise noted.

4.2. The endogeneity

The benchmark regression suffers from potential endogeneity challenges. Firstly, despite we have included relevant control variables, the limited cognitive scope makes it impossible to exhaust all factors influencing corporate green innovation, potentially leading to endogeneity due to omitted variables. Secondly, enterprises with stronger green innovation capabilities often exhibit a heightened sense of social responsibility. This can drive them to adopt AI technologies to enhance green innovation in response to government and social demands. As a result, the model may encounter the reverse causality problem. Finally, the decision of enterprises to utilize AI technologies is influenced by various factors such as their technological foundation, management strategies, financial position, and external environmental changes, which may result in sample selection bias. To address endogeneity arising from omitted variables and reverse causality, we employ the instrumental variable approach. For endogeneity caused by sample selection bias, we use the Heckman two-step method and propensity score matching (PSM) technique.

4.2.1. Instrument variable approach

Following Yao et al. (2024), we create an instrumental variable based on whether the listed company is located in a treaty port city from the Opium War to the end of the Qing Dynasty. Treaty port cities, known for their solid industrial foundation, favorable business environment, developed economic conditions, and open-mindedness, may affect the technology application and AI development in local enterprises. However, these factors do not directly influence the current green innovation level of local enterprises. As a result, the instrumental variable satisfies the requirements of relevance and exogeneity. Specifically, we define a dummy variable, *treatyport*, if the city where the enterprise is located has been established as a treaty port since the Opium War to the end of the Qing Dynasty, *treatyport* = 1, otherwise *treatyport* = 0. As our sample is a firm-year panel, and treaty port status does not change over time, we follow Nunn and Qian (2014) and use the interaction term between the one-period lag of the enterprise's AI level and *treatyport* as the instrumental variable (labeled *IV1*). Second, drawing on Yin et al. (2023), we calculate the average of other enterprises' AI within the enterprise's industry, and then use the cube of the enterprise's AI level to this average as an instrumental

variable (labeled *IV2*). The development of AI has peer effects, it is usually affected by other enterprises within the same industry, while the AI development level of other enterprises does not directly affect the enterprise's green innovation activities, making this instrumental variable relevant and exogenous.

Table 3 presents the two-stage least squares (2SLS) estimation results using instruments. The first-stage regressions in columns (1) and (4) demonstrate that *IV1* and *IV2* are both statistically significant at the 1% level for *AI*, verifying their relevance. Meanwhile, the Kleibergen-Paap rk LM test is significant at the 1% level, and both the Cragg-Donald Wald F statistic and Kleibergen-Paap rk Wald F statistic exceed the critical value of the Stock-Yogo weak identification test at the 10% level, indicating that the instruments do not suffer from under-identification and weak correlation issues. Columns (2) and (3) represent the second-stage regressions using *IV1*, while columns (5) and (6) show the second-stage regressions based on *IV2*. The results reveal that the IV estimates of the impact of IA on green innovation quantity (*griquan*) and quality (*griqual*) are positive at the 1% statistical level, indicating that the "incremental" and "qualitative" effects of AI on corporate green innovations remain significant after accounting for endogeneity.

Table 3

IV-2SLS estimation

Variable	(1) <i>AI</i>	(2) <i>griquan</i>	(3) <i>griqual</i>	(4) <i>AI</i>	(5) <i>griquan</i>	(6) <i>griqual</i>
<i>AI</i>		0.7837*** (0.1998)	0.6609*** (0.1832)		0.5420*** (0.0499)	0.1759*** (0.0460)
<i>IV1</i>	0.1560*** (0.0304)					
<i>IV2</i>				0.0546*** (0.0086)		
<i>_cons</i>	-1.9207*** (0.6488)			-1.3511*** (0.4259)		
<i>CVs</i>	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
KPLM	17.2558 [0.0000]			52.2344 [0.0000]		
CDF	107.9635			4497.9564		
KPF	26.3875 {16.38}			39.8725 {16.38}		
<i>N</i>	11072	11072	11072	13311	13311	13311

Note: KPLM denotes the Kleibergen-Paap LM statistic for the instrumental variable unidentification test. CDWF and KPWF denote the Cragg-Donald Wald F statistic and Kleibergen-Paap Wald F statistic for the instrumental variable weak identification test. The p-values for the KPLM test are in square brackets, and the critical values for the Stock-Yogo weak identification test at the 10% level are in braces.

4.2.2. Heckman Two-Step Method

Firstly, we set a dummy variable to differentiate enterprises that apply for AI patents from those that do not. Subsequently, a panel Probit model is utilized to estimate the probability of enterprises conducting AI technology research, i.e., the inverse Mills ratio (*IMR*). The *IMR* is then incorporated as a control variable in the benchmark model for estimation. The second-stage estimation results using the Heckman two-step method are presented in columns (1) and (2) of Table 4. The coefficients of *IMR* are statistically significant at the 1% level, indicating that the model suffers from endogeneity due to selection bias, and the marginal impact of *AI* on *griquan* and *griqual* remains positive at the 1% level. This implies that the results of AI enhancing the quantity and quality of corporate green innovations are robust and unaffected by sample selection bias.

4.2.3. Propensity Score Matching

The Heckman two-step method corrects for selection bias due to unobservable factors, and for the influences caused by observable factors, we use PSM to address this issue. Firstly, samples with independent variables (*AI*) greater than 0 are assigned a value of 1 to indicate the presence of AI technologies in the enterprise, and 0 otherwise. Subsequently, we treat all control variables as matching variables and use the nearest neighbor matching method to perform 1:1 matching on the sample. The re-estimation is then conducted using the matched sample. Columns (3) and (4) of Table 4 report the estimates after PSM³, which show that the impact of AI on the quantity and quality of corporate green innovation is consistent with the benchmark regression.

Table 4

Heckman two-step method and PSM estimation

Variable	(1)	(2)	(3)	(4)
	<i>griquan</i>	<i>griqual</i>	<i>griquan</i>	<i>griqual</i>
<i>AI</i>	0.3447*** (0.0207)	0.0799*** (0.0165)	0.3425*** (0.0265)	0.0477** (0.0186)
<i>IMR</i>	1.2013** (0.5997)	4.4053*** (0.8733)		
<i>_cons</i>	-3.3740* (1.7444)	-15.0737*** (2.5468)	-0.5689 (0.6704)	-3.6180*** (0.9756)
<i>CVs</i>	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
<i>R</i> ²	0.7605	0.9098	0.7446	0.9085
<i>N</i>	13476	13476	13477	13477

4.3. Robustness tests

4.3.1. Change the measurement of the dependent variable

Green patents granted to enterprises can demonstrate their commitment to green innovation and have a more substantial legal impact on the transition of innovation outcomes (Fabrizi et al., 2018). Therefore, we introduce *griquan_new*, which represents the quantity of corporate green innovation by taking the logarithm of the number of green patents granted to listed companies added one. We use the logarithm of the citations of green patents granted to listed companies added to one to measure the quality of corporate green innovation and represented as *griqual_new*. The results are reported in columns (1) and (2) of Table 5, showing that the positive effects of AI on both the quantity and quality of corporate green innovation remain significant.

4.3.2. Change the measurement of the independent variable

Word frequency analysis based on text data is an emerging quantitative statistical method that can provide insights into the level of attention given to a specific field or issue. To gauge the focus of listed companies on AI development, we conducted a study on the word frequency of AI-related keywords in their annual reports. Following the methodology outlined by Yao et al. (2024), we calculated the logarithm of the total word frequency added to one, as a proxy for the level of AI development in enterprises (labeled *AI_new*). The results are presented in columns (3) and (4) of Table 5. The significant and positive impact of *AI_new* on *griquan* and *griqual* at the 1% level are consistent with the benchmark regression.

Table 5

Robustness tests (I)

Variable	(1)	(2)	(3)	(4)
	<i>griquan_new</i>	<i>griqual_new</i>	<i>griquan</i>	<i>griqual</i>
<i>AI</i>	0.1965***	0.0760***		

³ See Appendix B for the hypothesis test of parallel conditions and the estimation of average treatment effects.

	(0.0215)	(0.0179)		
<i>AI_new</i>			0.0383*	0.0313**
			(0.0206)	(0.0147)
<i>_cons</i>	-2.0058***	-2.6137***	1.4259***	2.1642***
	(0.7563)	(0.94444)	(0.4563)	(0.1648)
<i>CVs</i>	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
<i>R</i> ²	0.7569	0.9297	0.7776	0.8940
<i>N</i>	10490	10490	9096	11986

4.3.3. Add Control Variables

Although the benchmark model includes relevant control variables, there may still be factors influencing corporate green innovation due to cognitive limitations. For example, by increasing R&D intensity, enterprises can promote green technology development, improve their innovation capability and competitiveness, and drive themselves in the direction of green, low-carbon, and sustainable development. Public attention towards environmental issues not only reflects shifts in green market demand, but also prompts stricter environmental regulations by governments, thereby increasing pressure on corporate environmental management and production operations. Government regulations, policies, standards, and measures aimed at environmental protection and pollution reduction also impact corporate green innovation. To more accurately assess the influence of AI on corporate green innovation, we take these factors into our model. For enterprise R&D intensity, it is measured by the ratio of enterprise R&D investment to operating revenue (labeled *rdt*). For public environmental attention, the logarithm of the Baidu index of environmental protection is employed (labeled *ea*). For governmental environmental regulation, it is calculated by constructing a comprehensive index based on industrial wastewater, exhaust gas and solid waste emissions in the city where the enterprise is located (labeled *er*). After incorporating these variables, the benchmark model is re-estimated, and the results are presented in columns (1) and (2) of Table 6. The findings demonstrate that AI continues to significantly enhance both the quantity and quality of corporate green innovation.

4.3.4. Control for high-dimensional fixed effects

There may be some unobserved factors at the industry and regional levels that could affect corporate green innovation in addition to the unobserved factors at the firm level. To exclude the interference of these factors, we further control for the fixed effects of the province and industry, as well as the interactive fixed effects of "province-year" and "industry-year" in the model. The estimation results are shown in columns (3) and (4) of Table 6. The coefficients of *AI* on *griquan* and *griqual* are still significantly positive at the 1% level, indicating the robustness of the benchmark results.

Table 6

Robustness test (II)

Variable	(1)	(2)	(3)	(4)
	<i>griquan</i>	<i>griqual</i>	<i>griquan</i>	<i>griqual</i>
<i>AI</i>	0.3058***	0.0480***	0.3293***	0.0499***
	(0.0191)	(0.0138)	(0.0206)	(0.0129)
<i>rdt</i>	0.4716**	0.4418		
	(0.2211)	(0.2708)		
<i>ea</i>	0.0149	0.0184		
	(0.0179)	(0.0175)		
<i>er</i>	0.6124	1.1214		
	(6.5806)	(5.8890)		
<i>_cons</i>	-0.3337	-3.9004***	-0.3744	-3.0688***
	(0.6577)	(0.9447)	(0.6515)	(0.7884)
<i>CVs</i>	YES	YES	YES	YES

Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Province FE	NO	NO	YES	YES
Industry FE	NO	NO	YES	YES
Province-Year FE	NO	NO	YES	YES
Industry-Year FE	NO	NO	YES	YES
R^2	0.7606	0.9265	0.7845	0.9331
N	11989	11989	13278	13278

4.3.5. Change estimation method

In the benchmark regression analysis, we assessed the influence of AI on corporate green innovation through a two-way fixed effects model. As there were instances of zero values for both the quantity and quality of corporate green innovation, aligning with the characteristics of the restricted model for the dependent variable, we proceeded to re-evaluate using the Tobit model. The estimation outcomes of the Tobit model are detailed in columns (1) and (2) of [Table 7](#). The coefficients of *griquan* and *griqual* are still significantly positive at the 1% level, confirming the robustness of the benchmark regression results.

4.3.6. Winsorize the data

To mitigate the impact of outliers in the sample on the model estimation, we winsorize all variables used in the regression by the upper and lower 5% quartiles. The model is re-estimated using the winsorized sample and the results are reported in columns (3) and (4) of [Table 7](#). The positive effect of *AI* on *griquan* and *griqual* is also significant after the winsorization of the sample, underscoring the robustness of the benchmark findings.

Table 7

Robustness tests (III)

Variable	(1) <i>griquan</i>	(2) <i>griqual</i>	(3) <i>griquan</i>	(4) <i>griqual</i>
<i>AI</i>	1.0142*** (0.0174)	0.3912*** (0.0131)	0.2858*** (0.0175)	0.0472*** (0.0139)
<i>_cons</i>	-1.8715*** (0.3438)	-7.6973*** (0.2481)	0.3129 (0.5947)	-2.3440** (0.9438)
<i>CVs</i>	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
R^2	0.1032	0.0706	0.7265	0.8952
N	13734	13734	13477	13477

4.3.7. Placebo test

To further ensure the reliability of our findings, we conduct a placebo test using a counterfactual framework. Following [Cantoni et al. \(2017\)](#), we randomly set the treatment group and repeat the regression for 500 times, and then analyze the parameter estimates of *AI* across these regressions and visualize the results in [Fig. 2](#) (the left and the right are the counterfactual estimates of *AI* on *griquan* and *griqual*, respectively). It is evident from the plot that the estimated coefficients of *AI* generated from the randomly created samples center around 0, while the actual coefficients obtained from the benchmark regression are 0.3453 and 0.0818 for *griquan* and *griqual*, respectively. Most of the estimated coefficients from the random sample have p-values greater than 0.05, indicating that the placebo test was successful. These results suggest that external factors have minimal impact on the benchmark model estimation and support the conclusion that AI positively influences corporate green innovation in a non-random manner, thereby confirming the robustness of our findings.

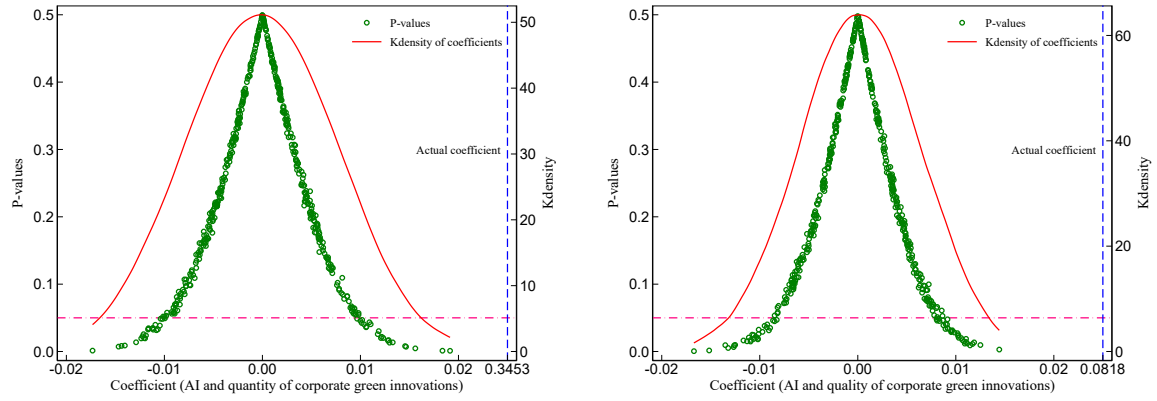


Fig. 2. Placebo Tests

5. Mechanism analysis

5.1. Increasing the accumulation of corporate human capital

Human capital plays a critical role in driving green innovation. Building on previous theoretical analysis, AI has been identified as a powerful tool in enhancing enterprises' human capital and fostering green innovation. To empirically test this channel, we use the ratio of R&D personnel within enterprises as a proxy for their human capital level (*hcl*). Following Yin and Wu (2023), we categorize samples with *hcl* values below the 25% quantile as low human capital enterprises (*Lowhcl*), assigning a value of 1 to the corresponding dummy variable *Lowhcl* and 0 otherwise. Additionally, we introduce an interaction term between AI and low human capital enterprises (*AI*×*Lowhcl*). The results are presented in Table 8, revealing that the effects of *Lowhcl* on both *griquan* and *griqual* are significantly negative at the 1% level. The coefficients of the interaction term (*AI*×*Lowhcl*) are significantly positive at the 5% level, suggesting that AI has a more pronounced effect on promoting green innovations in low human capital enterprises compared to those with high human capital. These findings provide empirical support for the theoretical proposition that AI enhances corporate green innovation by bolstering human capital accumulation.

Table 8

Mechanism test: Increasing human capital

Variable	<i>griquan</i>	<i>griqual</i>
<i>AI</i>	0.3366*** (0.0209)	0.0718*** (0.0171)
<i>Lowhcl</i>	-0.0758** (0.0300)	-0.0936*** (0.0359)
<i>AI</i> × <i>Lowhcl</i>	0.0580* (0.0329)	0.0660*** (0.0250)
<i>_cons</i>	-0.1843 (0.6123)	-3.4693*** (0.9635)
<i>CVs</i>	YES	YES
Firm FE	YES	YES
Year FE	YES	YES
<i>R</i> ²	0.7607	0.9093
<i>N</i>	13477	13477

5.2. Enhancing the efficiency of corporate management

AI improves enterprise management efficiency through data analysis, decision support, automated processes, and cost control, and aiding enterprises operating efficiency. The efficiency improvement optimizes resource utilization,

standardizes management systems, and fosters green innovation. To investigate how AI promotes corporate green innovation by boosting management efficiency, we use the ratio of administrative and selling expenses to total operating revenue as a measure of enterprise management efficiency (*mef*), with the larger value representing the lower management efficiency of an enterprise. Similarly, enterprises with *mef* values above the 75% quartile are defined as low managerial efficiency enterprises (*Lowmef*), and the corresponding dummy variable takes the value of 1, otherwise 0. On this basis, we introduce an interaction term between AI and low managerial efficiency enterprises (*AI*×*Lowmef*). The estimation results are presented in Table 9. The coefficients of *Lowmef* for *griquan* and *griqual* are both negative and statistically significant at the 1% level. The coefficients of the interaction term *AI*×*Lowmef* are significantly positive at the 1% level, suggesting that inefficient management hinders green innovation development, while AI enhances enterprise managerial efficiency and positively impacts the quantity and quality of green innovation. This confirms the theoretical mechanism that AI promotes corporate green innovation by enhancing managerial efficiency.

Table 9

Mechanism testing: Enhancing management efficiency

Variable	<i>griquan</i>	<i>griqual</i>
<i>AI</i>	0.1005*** (0.0164)	0.0413*** (0.0138)
<i>Lowmef</i>	-0.0503* (0.0273)	-0.0905*** (0.0275)
<i>AI</i> × <i>Lowmef</i>	0.1389*** (0.0248)	0.0395* (0.0219)
<i>_cons</i>	0.2815 (0.7231)	2.7527*** (0.3931)
<i>CVs</i>	YES	YES
Firm FE	YES	YES
Year FE	YES	YES
<i>R</i> ²	0.7392	0.8964
<i>N</i>	10007	11072

5.3. Improving the quality of corporate environmental information disclosure

According to theoretical analysis, AI has the potential to enhance the quality of corporate environmental information disclosure, thereby promoting corporate green innovation. To investigate this mechanism, we construct a corporate environmental information disclosure index based on the annual reports of listed companies, employing both qualitative and quantitative methods. We define enterprises with values below the 25th percentile as low disclosure quality enterprises (*Loweid*), assigning a dummy variable that takes the value of 1 for these enterprises and 0 otherwise. We introduce the interaction term (*AI*×*Loweid*) to explore the relationship between AI and low disclosure quality. The results are presented in Table 10, both quantitatively and qualitatively, the coefficients for *Loweid* and *AI*×*Loweid* are significantly negative and positive at the 1% level, respectively. This suggests that AI has a more pronounced facilitating effect on the green innovation of enterprises with low environmental information disclosure quality compared to those with high disclosure quality. In other words, AI enhances the environmental disclosure quality of enterprises, which subsequently amplifies the green innovation effect. Thus, the mechanism related to information disclosure is confirmed.

Table 10

Mechanism testing: Improving environmental information disclosure

Variable	<i>griquan</i>	<i>griqual</i>
<i>AI</i>	0.1168*** (0.0183)	0.0586*** (0.0136)
<i>Lowmef</i>	-0.0740*** (0.0221)	-0.0571*** (0.0220)
<i>AI</i> × <i>Lowmef</i>	0.1025***	0.0415**

	(0.0246)	(0.0208)
<i>_cons</i>	0.5038	-1.1571
	(0.7140)	(1.0015)
<i>CVs</i>	YES	YES
Firm FE	YES	YES
Year FE	YES	YES
<i>R</i> ²	0.7341	0.9163
<i>N</i>	11072	11072

6. Heterogeneity Analysis

6.1. The ownership of the enterprises

State-owned enterprises (SOEs) are funded by the government, and receive financial backing from the national finance, bank credit, capital market and other sources. Non-state-owned enterprises (non-SOEs) are privately owned and operate autonomously, relying on self-financing, bank loans, investment funds and similar avenues for funding. To investigate potential differences in the impact of AI on green innovation between these two types of enterprises, we conducted a group regression by dividing the sample into SOEs and non-SOEs. The results are presented in Table 11. According to columns (1) and (2), the effects of AI on *griquan* are significantly positive at the 1% level and pass the inter-group difference test, suggesting that AI has a greater facilitating effect on the quantity of green innovation in SOEs compared to non-SOEs. Similarly, columns (3) and (4) indicate that the effect of AI on the quality of green innovation in SOEs is greater than that observed in non-SOEs. One potential reason is that SOEs benefit from diverse and relatively low-cost financing channels, ensuring that their R&D funds are both sufficient and stable (Liu et al., 2024), thereby significantly advancing the development and application of AI. Another reason is that SOEs have established superior talent cultivation and protection systems, which facilitate the attraction and retention of skilled professionals, thus providing essential intellectual support for the advancement of AI technologies. In addition, SOEs exhibit heightened sensitivity to national policies regarding green development and digital science and technology (S&T), and they possess enhanced capabilities for policy implementation and resource allocation. This responsiveness enables them to swiftly address and enact relevant policy requirements, thereby enhancing the role of AI in fostering green innovation.

Table 11

Heterogeneity test: Based on the ownership of enterprises

Variable	<i>griquan</i>		<i>griqual</i>	
	(1) SOEs	(2) Non-SOEs	(3) SOEs	(4) Non-SOEs
<i>AI</i>	0.3905*** (0.0319)	0.2962*** (0.0273)	0.1155*** (0.0267)	0.0504** (0.0205)
<i>_cons</i>	0.5998 (0.9928)	-1.5093* (0.8067)	-3.0615** (1.3241)	-4.4749*** (1.3040)
<i>CVs</i>	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
<i>R</i> ²	0.7903	0.7392	0.9196	0.9035
<i>N</i>	6022	7387	6022	7387
Bdiff test	p-value = 0.0000		p-value = 0.0000	

6.2. The scale of enterprises

Enterprises of different sizes differ significantly in terms of resource inputs, technological innovation, and management strategies. We categorize enterprises based on their total assets, designating those at or above the 75th

percentile as large-scale enterprises (LSEs), while the remainder are classified as small and medium enterprises (SMEs). The results of the grouped regression analysis are presented in Table 12. The coefficients of *AI* on *griquan* and *griqual* are significantly positive for both LSEs and SMEs. However, the impact of *AI* on *griquan* and *griqual* is more pronounced in LSEs than in SMEs, indicating that AI plays a more critical role in driving green innovation in LSEs, both quantitatively and qualitatively. This is because the powerful resource allocation capacity and well-established organizational structure of LSEs enable them to adopt and integrate AI technologies more swiftly. Also, LSEs possess robust risk management systems that effectively assess and respond to risks associated with the application of AI technologies, thereby allowing them to undertake bolder initiatives in the realm of green innovation (Dong et al., 2024). Moreover, LSEs benefit from extensive partner networks, including research organizations, suppliers, and customers, which facilitate access to a broader range of external resources for AI technology development and green innovation.

Table 12

Heterogeneity test: Based on the scale of enterprises

Variable	<i>griquan</i>		<i>griqual</i>	
	(1) LSEs	(2) SMEs	(3) LSEs	(4) SMEs
<i>AI</i>	0.4652*** (0.0368)	0.2623*** (0.0199)	0.0895*** (0.0227)	0.0374** (0.0174)
<i>_cons</i>	-5.6142** (2.3762)	-0.4758 (0.6625)	-2.8640 (2.5935)	-5.5777*** (0.9326)
<i>CVs</i>	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
<i>R</i> ²	0.8396	0.7155	0.9432	0.8975
<i>N</i>	3338	10024	3338	10024
Bdiff test	p-value = 0.0000		p-value = 0.0467	

6.3. Policy preference

The establishment of the National New Generation AI Innovation and Development Pilot Zone represents a significant policy initiative by the Chinese government aimed to promote AI development. To assess whether there is a difference in the green innovation effect of AI under varying levels of policy support, we categorize the sample into two groups: AI innovation pilot zones ("pilot zones") and non-AI innovation pilot zones ("non-pilot zones"). The results are reported in Table 13. As illustrated in columns (1) and (2), the impact of AI on green innovation is significantly positive at the 1% level and passes the inter-group difference test. This indicates that AI contributes more substantially to the quantity of corporate green innovation in pilot zones compared to non-pilot zones. This disparity may be attributed to the concentration of high-tech enterprises and research institutions in pilot zones, which are better equipped for the research and application of cutting-edge technologies, such as AI. Moreover, pilot zones benefit from enhanced policy and resource support, creating more favorable conditions for enterprises to apply AI in promoting green innovation. Columns (3) and (4) present the impact of AI on the quality of corporate green innovation. While the coefficient of *AI* on *griqual* is significantly positive at the 5% level, it does not pass the inter-group difference test. This suggests that the positive effect of AI on the quality of corporate green innovation is consistent across both pilot and non-pilot zones. This may be attributed to the fact that the establishment of pilot zones primarily occurred between 2019 and 2021, with over 60% of enterprises being incorporated into these zones after 2020. Given this short time and the improvements in the quality of green innovation typically reflect in longer term (Alsaggaf, 2024), it is too early to conclude whether AI is more effective in enhancing the quality of green innovation for enterprises in pilot zones compared to those in non-pilot zones.

Table 13

Heterogeneity test: Based on policy preference

Variable	<i>griquan</i>		<i>griqual</i>	
	(1)	(2)	(3)	(4)

	Pilot zones	non-Pilot zones	Pilot zones	non-Pilot zones
<i>AI</i>	0.3028*** (0.0229)	0.2629*** (0.0267)	0.0385** (0.0182)	0.0528** (0.0211)
<i>_cons</i>	1.0283 (0.8513)	-0.5499 (0.8320)	-2.1481 (1.4058)	-2.0633 (1.2665)
<i>CVs</i>	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
<i>R</i> ²	0.7356	0.7175	0.8961	0.8958
<i>N</i>	7027	6442	7027	6442
Bdiff test	p-value = 0.0633		p-value = 0.3100	

7. Further discussions

7.1. Diffusion effect or crowding-out effect?

Based on the previous analysis, we can conclude that AI has a significant positive impact on green innovation. There are two pathways for corporate green innovation: one involves using AI to facilitate the diffusion of general innovation activities towards green innovation, while the other crowds out other innovation activities in favor of green innovation. The "diffusion effect" refers to the phenomenon where enterprises increase their internal investments in innovation and pursue green innovation alongside the expansion of their existing activities. AI markedly enhances the efficiency of R&D activities through data analytics tools and automation technologies, prompting enterprises to boost their R&D investments. The "crowding-out effect" refers to that, enterprises shift their limited resources to green innovation projects while reducing other innovative activities. Particularly when confronted with pressures such as rising operating costs, social responsibility, and policy and regulatory demands, companies reallocate their limited resources towards to green development.

To examine the diffusion effect, we employ enterprises' innovation input and output as explained variables and performed a regression analysis using two-way fixed effects. The advancement of AI has generated a demand for professionals with data science skills, prompting companies to invest in human capital (Liu et al., 2020). We use research and development investment (*rd*) and the number of individuals engaged in research and development (*hrd*) as measures for green innovation input, and use the natural logarithm of the total number of patent applications (plus 1) as the innovation output (*innov*). The estimation results are presented in columns (1) to (3) of Table 14. The coefficients of *rd*, *hrd* and *innov* are positive and statistically significant at the 1% level, indicating that AI enhances enterprise innovation and shows a diffusion effect. To investigate the crowding-out effect, we employ the efficiency of corporate resource allocation (*eff*), calculated using the DEA model, as an indicator. The results are displayed in column (4) of Table 14. The coefficient of *AI* on *eff* is not statistically significant, suggesting that the development of AI did not result in resource reallocation within firms, and that green innovation did not crowd out other innovative activities. In conclusion, the impact of AI on enterprise green innovation is primarily driven by the diffusion effect rather than the crowding-out effect.

Table 14

Results for the further discussion

Variable	(1) <i>rd</i>	(2) <i>hrd</i>	(3) <i>Innov</i>	(4) <i>eff</i>	(5) <i>IR</i>
<i>AI</i>	0.0234** (0.0106)	0.0165*** (0.0045)	0.1690*** (0.0540)	-0.0067 (0.0075)	0.0144*** (0.0030)
<i>_cons</i>	1.5984* (0.8683)	-4.1398*** (0.5930)	-0.0793 (2.4547)	-1.1147 (0.9153)	4.7190*** (0.1947)
<i>CVs</i>	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

R^2	0.8925	0.9744	0.5922	0.2131	0.2531
N	12304	13477	7313	13024	4630

7.2. The impact of AI on corporate green innovation resilience

The term "green innovation resilience" refers to the capacity of enterprises to endure external pressures that may hinder the continuation of green technology research and development, while also achieving further breakthroughs in green innovation amid environmental changes and crises. The contemporary era is witnessing a significant and profound transformation. The anti-globalization movement is experiencing heightened tensions, the economic landscape is marked by turbulence, climate-related risks are intensifying, and a multitude of unforeseen events, including "black swan" and "grey rhino" occurrences, may arise at any moment. Consequently, the study of corporate green innovation resilience has become particularly important. Previous research indicates that AI can enhance corporate green innovation. It is also essential to investigate whether this green innovation effect can be sustained when faced with external shocks. In this context, we calculate the green innovation resilience index following [Martin and Gardiner \(2019\)](#). The formula is as follows.

$$IR_{i,t} = (\Delta Y_{i,t} - \Delta E_{i,t}) \div |\Delta E_{i,t}| \quad (3)$$

$$\Delta Y_{i,t} = Y_{i,t} - Y_{i,t-1} \quad (4)$$

$$\Delta E_{i,t} = [(Y_{r,t} - Y_{r,t-1}) \div Y_{r,t-1}] \times Y_{i,t-1} \quad (5)$$

Where IR represents corporate green innovation resilience, and Y denotes the green patent application of enterprises. ΔY is the annual change in green patent applications. $\Delta E_{i,t}$ refers to the predicted change in green patent applications for enterprise i from year $t-1$ to year t based on the change in green patent applications in city r where enterprise i is located. To ensure the interpretability of the empirically determined coefficients, it is essential to apply the natural logarithm after adding 100 to the green innovation resilience. The results are reported in column (5) of [Table 14](#). The coefficient of AI on IR is significantly positive, suggesting that AI can enhance the resilience of corporate green innovation. This can be attributed to two main factors. First, innovation is a fundamental component in developing resilient systems that can effectively respond to risks while remaining autonomous and controllable. When AI successfully promotes corporate green innovation, it inevitably contributes positively to the resilience of these initiatives. Second, AI facilitates real-time monitoring of corporate operations, allowing for the effective identification of organization-specific challenges in green innovation activities and enabling the implementation of timely corrective measures. As a result, AI enhances the effectiveness of corporate green innovation activities and strengthens their ability to withstand external risks.

8. Conclusions and implications

This study investigates the effects and mechanisms of artificial intelligence (AI) on corporate green innovation, using a panel data of listed companies in China from 2007 to 2021. Our main findings are as follows: First, AI significantly promotes corporate green innovation. The empirical results indicate that AI facilitates corporate green innovation on both quantity and quality. Second, internal governance serves as a mechanism through which AI influences corporate green innovation. Specifically, AI fosters corporate green innovation by increasing human capital accumulation, enhancing management efficiency, and improving the quality of environmental information disclosure. Third, the effects of green innovation driven by AI are multi-dimensional and heterogeneous. In terms of enterprise ownership, AI contributes more significantly to green innovation in SOEs compared to non-SOEs. When considering enterprise scale, the green innovation effects generated by AI are more pronounced in LMEs than in SMEs. Regarding policy preferences, the positive impact of AI on the quantity of corporate green innovations is more substantial in pilot zones than in non-pilot zones; however, the effect on the quality of green innovations does not vary significantly with the intensity of policy support. Fourth, the influence of AI on corporate green innovation is characterized more by a diffusion effect than a crowding-out effect, further promoting sustainable development in green innovation by enhancing overall corporate innovation. Finally, AI aids in bolstering the resilience of corporate green innovation, enabling it to continue fostering green innovation in the

face of external shocks and challenges.

Based on the above findings, we propose the following policy implications.

Firstly, the development and application of AI technologies should be enhanced to strengthen the digital foundation of corporate green innovation. Governments should formulate and implement policies that encourage the use of AI in green innovation, such as tax incentives, innovation funds, and R&D subsidies, to motivate enterprises to adopt AI technologies. It is crucial to promote cross-border cooperation and enhance the innovation ecosystem involving various market entities. Additionally, accelerating the application of AI in green technological research through knowledge and resource sharing is essential. Efforts should also focus on improving public awareness, education, and training in the field of AI and green technologies to provide talent support and knowledge reserves for enterprises aiming to leverage AI for driving green innovation.

Secondly, differentiated policies should be developed in collaboration with various enterprises to utilize the impact of green innovation driven by AI, tailored to local circumstances. SOEs should be encouraged to innovate in sectors such as clean energy and waste management. Non-SOEs should receive tax incentives and financial subsidies to advance AI technology and the development of green products through partnerships with the public sector. LMEs should be incentivized to capitalize on their size advantage by investing in AI research and applications to facilitate the dissemination of green technologies. SMEs should receive specialized technical support and training to help them overcome the challenges associated with adopting AI technology. In the pilot zones, enterprises should fully utilize the available policy conditions to boldly explore new AI technologies, thereby enhancing the demonstration effect that empowers green innovation. In non-pilot zones, enterprises should be encouraged to proactively engage in industry-university-research cooperation and to acquire advancements in AI technologies through imitation and learning.

Thirdly, the channels through which AI can promote corporate green innovation must be clearly defined by optimizing internal corporate governance. In terms of human capital accumulation, governments should establish a widespread education and training programs related to AI and green technologies in conjunction with social organizations. Enterprises should be encouraged to engage in training and education focused on AI, sustainable development, and environmental management. Regarding organizational management, the government should assist enterprises in enhancing their green supply chains and encourage the adoption of intelligent data analysis and machine learning technologies to optimize decision-making processes. Additionally, it is necessary to clarify the standards for corporate environmental information disclosure and to establish effective incentives and constraints to motivate enterprises to improve their information disclosure quality.

Fourth, the diffusion effect of AI should be enhanced, and the resilience of enterprises in green innovation should be strengthened. On one hand, it is essential to promote the overall innovation level of enterprises. This can be achieved by providing policy support for enterprise innovation through financial incentives, taxation, procurement, and other means; strengthening the development of AI-related disciplines and talent cultivation to create a robust talent pool for enterprise R&D; and improving the intellectual property rights protection system to safeguard the achievements of enterprise innovation. On the other hand, it is crucial to enhance enterprises' awareness of innovation risk response and prevention. Enterprises should establish a risk assessment system to identify and analyze the potential risks and their impacts that may arise during the process of green innovation. Furthermore, they should formulate corresponding strategies for risk prevention, risk transfer, risk mitigation, and risk acceptance in response to the identified risk factors.

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