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UNLOCKING CORPORATE GREEN TECHNOLOGICAL INNOVATION WITH ARTIFICIAL INTELLIGENCE: THE MODERATING IMPACT OF CEO GREEN EXPERIENCE

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Abstract: Amid escalating global environmental challenges, understanding how technological advancements drive sustainable innovation has become a critical topic. This study empirically examines the impact of artificial intelligence (AI) adoption on corporate green technological innovation using a sample of Chinese-listed companies from 2010 to 2023. The findings indicate that AI adoption significantly enhances green innovation performance. Additionally, the CEO green experience positively moderates the relationship between AI and green innovation, amplifying AI's positive impact. Furthermore, internal control quality and R&D investment are identified as mediating mechanisms through which AI influences green innovation, unveiling the internal pathways through which AI fosters sustainable innovation. By revealing these mechanisms, this study deepens the understanding of how AI drives sustainability within corporate structures. It not only provides empirical evidence on AI's role in promoting green innovation at the firm level but also highlights the importance of executives' environmental awareness and the roles of internal control and R&D investment. These findings carry significant practical implications for companies aiming to achieve sustainability through AI and for policymakers seeking to promote green innovation through technological advancements.
Keywords: Artificial Intelligence; Green technological innovation; CEO green experience; Sustainable innovation; Corporate social responsibility

1 INTRODUCTION

Below is the revised text with APA-style citations replaced by sequential numeric citations in the format [1-6,8], following the order of appearance as established in the reference list provided earlier. The references are numbered based on their first mention in the text.

Considering the growing global challenges of climate change and environmental pollution, promoting sustainable development has become a shared goal for the international community [1]. The signing of international agreements such as the Paris Agreement highlights the global emphasis on environmental protection and climate change [2]. As key players in economic activities, corporations are not only major contributors to resource consumption and pollution but also crucial drivers of green transformation and technological innovation [3]. Green technological innovation, defined as the development and application of environmentally friendly technologies to reduce environmental impact and foster coordinated economic and environmental growth [4], not only helps lower pollution and resource consumption but also creates new market opportunities and competitive advantages for businesses [5]. For instance, companies developing energy-saving technologies often gain a competitive edge under increasingly stringent environmental regulations [6]. However, how to effectively foster green technological innovation within firms remains a pressing issue [7].

Artificial Intelligence (AI), as a driving force behind the latest technological revolution and industrial transformation, is profoundly reshaping production processes and business models across various sectors [8]. With its capabilities in data analysis, pattern recognition, and autonomous learning, AI offers unprecedented opportunities for corporate innovation [9]. It enables firms to better identify market demands, optimize resource allocation, and improve production efficiency, thus supporting green technological innovation [10]. For example, AI applications in manufacturing allow for smart production and precise control, leading to reduced energy and raw material consumption [11]. In the energy sector, AI can optimize energy management systems and enhance the efficiency of renewable energy utilization [12]. However, the specific ways in which AI impacts green technological innovation and the mechanisms behind this influence are still underexplored.

At the same time, the background and characteristics of top executives play a critical role in corporate strategic decisions [13]. Upper Echelons Theory suggests that a manager's values, cognition, and experiences shape the firm’s perception of the external environment and strategic choices [14]. CEOs with green experience are particularly likely to prioritize environmental protection and sustainable development, supporting eco-friendly projects and green technology development [15]. These CEOs may pay greater attention to environmental performance and respond more proactively to environmental regulations and market demands for green initiatives [16]. Their environmental awareness and values could strengthen AI’s role in driving green technological innovation, accelerating the company’s green transition [17]. Therefore, examining the role of CEO green experience in AI's impact on green technological innovation has significant theoretical and practical relevance.

Additionally, the quality of internal controls and R&D investment are important factors influencing green technological innovation [18]. High-quality internal controls ensure effective strategy implementation, reduce risks, and improve operational efficiency [19]. A robust internal control system facilitates the efficient allocation of resources, supporting sustained investment in green technology R&D [20]. Adequate R&D investment, in turn, provides the financial resources necessary for technological innovation [21]. However, R&D activities are often high-risk and uncertain, requiring strong risk management and innovation capabilities from firms [22]. AI could further enhance green technological innovation by improving internal control quality and increasing R&D investment [23]. For example, AI can boost internal control effectiveness through automated audits and real-time risk monitoring [24]. It also helps firms more accurately assess the risks and returns of R&D projects, optimizing R&D resource allocation. However, the specific mechanisms through which these channels affect the relationship between AI and green technological innovation require further research.

The focus on Chinese-listed companies as the research sample is particularly significant in this study. First, China, as the world's second-largest economy and largest developing country, is in a rapid phase of industrialization and urbanization, facing immense energy consumption and environmental pressures [25]. Chinese firms play a significant role in global carbon emissions and resource consumption, making them critical to global environmental governance [26]. Second, the Chinese government places strong emphasis on green development and technological innovation, implementing various policies to encourage companies to pursue green technological innovation and adopt AI [27][28]. This policy environment provides a unique backdrop for studying AI's role in corporate green technological innovation. Lastly, Chinese-listed companies offer high data availability and transparency, with their business scale and industry distribution being representative, enhancing the reliability and generalizability of the research findings [29]. Thus, exploring the impact of AI on green technological innovation in Chinese-listed firms not only enriches the theoretical literature but also offers practical insights for companies in China and other emerging economies.

This study advances the existing literature in three contributions: (1) It empirically tests the direct impact of AI on green technological innovation at the firm level. Previous research has mostly focused on AI's macro-level applications or its influence on overall innovation capacity, with limited empirical analysis of how AI specifically promotes green technological innovation within firms. This paper, using a sample of Chinese listed companies, offers a deeper exploration of AI's role in driving green innovation at the firm level, contributing to the intersection of AI and sustainability studies, and providing fresh insights into how firms can harness AI for green innovation. (2) It uncovers the moderating effect of CEO green experience on the relationship between AI and green technological innovation. While existing research has rarely explored how executive characteristics influence the outcomes of AI applications, this study introduces the Upper Echelons Theory to examine how CEOs with green experience enhance AI's role in promoting green technological innovation. It highlights the pivotal role of executive environmental awareness in shaping the use of technology and fostering green innovation, filling a gap in the literature on leadership traits and green innovation. (3) It elucidates the mediating mechanisms of internal control quality and R&D investment in AI's promotion of green technological innovation. By analyzing the channels through which internal control and R&D investment operate, the paper delves into the underlying mechanisms of AI's impact on green innovation. This approach not only deepens the understanding of AI's pathways but also provides theoretical support for firms aiming to improve internal controls and optimize R&D resource allocation to enhance green innovation capabilities.

The remainder of this paper is organized as follows: Section 2 reviews the literature relevant to our study. Section 3 describes the data and methodology employed. Empirical findings and discussion are presented in Sections 4 and 5. Finally, Section 5 offers conclusive remarks and summarizes the key insights of the paper.

2 LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 AI and Green Technological Innovation

In recent years, the impact of Artificial Intelligence (AI) on corporate innovation and sustainable development has garnered widespread attention [30]. However, research on how AI specifically fosters green technological innovation at the firm level remains relatively underexplored, which presents a critical gap and research opportunity for this study.

Numerous scholars have examined the influence of AI on corporate innovation capabilities. Johnson et al. (2022) found that firms utilizing AI technology exhibit exceptional performance in patent output and technological breakthroughs, suggesting that AI can effectively accelerate the process of technological innovation [31]. Similarly, Brem et al. (2021) highlighted that AI, as a general-purpose technology, is reshaping corporate innovation models [32]. Meanwhile, the drivers of green technological innovation have also attracted significant attention. Huang and Huang (2024) pointed out that government environmental policies, market pressure for green demand, and internal resource allocation within firms are the primary driving forces behind green technological innovation [33]. These factors, viewed from both external and internal perspectives, underscore the complexity of green innovation.

The resource-based view (RBV) emphasizes that a firm's unique resources and capabilities are the sources of its competitive advantage [34]. As an emerging and scarce technological resource, AI enhances firms' innovation capabilities, particularly in the green technology domain [35]. Firms equipped with AI can leverage precise technological analysis and optimized resource allocation to drive the development and application of green technologies. Additionally, the dynamic capabilities theory suggests that firms can maintain competitive advantages in a rapidly changing environment by continuously adjusting and reconfiguring their resources and capabilities [36]. AI endows firms with the agility to swiftly respond to environmental regulations and market demand for green technologies, thereby facilitating technological innovation [37].

Moreover, regarding the relationship between AI and sustainable development goals, Kulkov et al. (2024) explored AI's applications in environmental monitoring, pollution control, and resource management, asserting that AI can significantly contribute to achieving global sustainability objectives [38]. However, these studies are predominantly conducted at the macro level, lacking in-depth analysis of specific pathways for green technological innovation at the firm level. To address this research gap, the present study investigates how AI directly influences green technological innovation within firms. Based on the above analysis, this study proposes the following hypothesis:

H1: Artificial Intelligence significantly promotes green technological innovation within firms.

2.2 The Moderating Role of CEO Green Experience

Against the backdrop of escalating global environmental challenges, the role of firms in driving green technological innovation has become increasingly critical. Artificial Intelligence (AI), as a significant tool for promoting green technological innovation, has garnered widespread attention. However, the impact of AI on green innovation may vary depending on the characteristics of corporate leaders.

Upper Echelons Theory posits that the background, values, and experiences of top executives profoundly influence their strategic decisions and organizational performance [39]. CEOs with green experience are more likely to prioritize environmental protection and sustainable development, directly influencing their support for and application of AI in green innovation [40]. These CEOs may be more inclined to allocate resources towards AI-driven green technology research and development, seeking to achieve a win-win outcome for both environmental and economic benefits [41]. Social Cognitive Theory further corroborates this view. Mischel (1973) emphasizes that individuals' past experiences and social environments shape their cognitive and behavioral patterns [42]. CEOs with green experience are likely to advocate for environmental initiatives within their firms and actively support the application of AI in green innovation [43]. They may also be more proactive in collaborating with external environmental organizations and technological institutions to access the latest green technologies and knowledge.

Empirical research supports the theoretical perspectives mentioned above. Arena et al. (2018) found that CEOs with environmental backgrounds are more inclined to support technological innovation, particularly green technological innovation [44]. Shu et al. (2020) noted that CEOs' environmental awareness enhances firms' receptivity to new technologies, thereby improving green innovation performance [45]. Quan et al. (2021) further demonstrated that CEOs with green experience reinforce the positive impact of environmental regulations on green innovation, indicating that when CEOs have green experience, the effect of environmental regulations on green innovation becomes more pronounced [46].

Based on the above analysis, it can be inferred that CEOs' green experience may influence firms' AI adoption strategies, thereby enhancing AI's contribution to green technological innovation. CEOs with green experience are more likely to integrate AI into green innovation strategies, leading to higher levels of green technological innovation. This not only improves firms' environmental performance but also strengthens their competitive advantage and social reputation. Thus, the following hypothesis is proposed:

H2: CEOs' green experience positively moderates the impact of Artificial Intelligence on green technological innovation.

2.3 The Mechanism of Internal Control Quality and R&D Investment

2.3.1. The Impact of AI on Internal Control Quality and Its Role in Green Technological Innovation

Internal control quality refers to the effectiveness of a set of policies and procedures established by firms to ensure the reliability of financial reporting, operational efficiency, and regulatory compliance [47]. High-quality internal control enhances firms' operational efficiency, risk management capabilities, and information transparency, thereby promoting sustainable development [48].

The application of AI technologies can significantly improve internal control quality. On one hand, AI leverages big data analytics and machine learning to monitor and identify potential risks and irregularities in real time, strengthening firms' risk management capabilities [49]. On the other hand, AI automates internal auditing processes, improving both audit efficiency and accuracy while reducing human error [50].

High-quality internal control facilitates green technological innovation. Robust internal control ensures efficient resource allocation, thereby supporting investment in green technology R&D [51]. Moreover, enhanced internal control improves the quality of environmental information disclosure, bolstering a firm's environmental image and social responsibility, which further incentivizes green innovation [52]. Based on this analysis, we propose the following hypothesis:

H3a: AI promotes green technological innovation by improving internal control quality.

2.3.2. The Impact of AI on R&D Investment and Its Role in Green Technological Innovation

R&D investment is a key driver of technological innovation. Sufficient R&D funding provides the necessary financial and resource support for green technological innovation [53]. However, R&D activities often involve high risk and uncertainty, which may result in financial constraints and uncertainties regarding investment returns.

The application of AI technologies can influence firms' R&D investment decisions. On one hand, AI improves operational efficiency and profitability, enabling firms to generate more internal funds for R&D activities [54]. On the other hand, AI's data analytics and predictive models help firms more accurately assess the potential benefits and risks of R&D projects, optimizing the allocation of R&D resources [55].

Increased R&D investment drives green technological innovation. Greater financial support enables firms to develop new green products and processes, enhancing their innovation capabilities and market competitiveness [56]. Additionally, increased R&D investment fosters collaboration between firms and research institutions or universities, enabling access to cutting-edge green technology knowledge [57]. Based on this analysis, we propose the following hypothesis:

H3b: AI promotes green technological innovation by increasing R&D investment.

3 METHODOLOGY

3.1 Data and Sample

This study focuses on Chinese A-share listed companies from 2010 to 2023, as 2010 marked a pivotal year in the development of AI technology and industry in China. With breakthroughs in big data, cloud computing, and deep learning [57], AI entered a period of rapid growth. Simultaneously, the Chinese government introduced a series of supportive policies, such as the Decision on Accelerating the Cultivation and Development of Strategic Emerging Industries (2010) and the New Generation Artificial Intelligence Development Plan (2017) [58,59]. These policies created a favorable environment for AI adoption and green technological innovation within firms. Therefore, selecting 2010 as the starting year allows us to capture the dynamics of AI's influence on green innovation, while 2023 provides the most recent available data, ensuring the study's relevance and comprehensiveness. By analyzing data from 2010 to 2023, we can evaluate the long-term impact of AI on green innovation and track its development over time.

The study sample includes A-share listed companies from the Shanghai and Shenzhen stock exchanges, with data sourced from various channels. Financial and governance data were obtained from the CSMAR database, while AI-related patents were collected through the China National Intellectual Property Administration (CNIPA) using keyword searches and International Patent Classification (IPC) codes. Green innovation data were similarly sourced through CNIPA using green patent classification guidelines. CEO information, including educational background and work experience, was manually gathered from annual reports and company announcements to identify CEOs with green experience (CGE). To ensure data quality, financial firms were excluded due to their unique accounting standards and regulatory environment. Missing and outlier data were removed, and continuous variables were Winsorized at the 1% and 99% levels to reduce the influence of extreme values. The model also controlled for industry and year fixed effects, using the China Securities Regulatory Commission’s industry classification standards. After screening, the final sample comprised 32,820 firm-year observations, representing key industries such as manufacturing, services, and high-tech sectors, with broad representativeness.

3.2 Variables of Study

3.2.1 Independent variable

The independent variable in this study is the level of AI application (AI). Drawing on previous research [59-61], we measure AI applications by the number of AI-related patents filed annually by listed companies. These patents represent the AI technologies possessed by the companies [62] and serve as an indicator of their AI output. This can be cross-referenced with annual reports to further verify the company’s AI capabilities. Data on the titles, abstracts, application dates, applicants, and classification numbers of patents filed by Chinese-listed companies were obtained from the Intellectual Property Rights Database (IRPDB). Using applicant information, we matched the patents to their respective companies and identified AI-related patents through keyword searches in the titles and abstracts. These patents were categorized as AI patents. To quantify a company's AI application level (AI), we calculated the natural logarithm of the number of AI patents filed each year plus one (Lnpatents).

3.2.2 Dependent variable

Additionally, we measure corporate green technological innovation (Green) by referencing [63] and using the number of green patent applications. Specifically, the number of green utility model patent applications measures the quantity of green innovation (GreNum), while the number of green invention patent applications represents the quality (GreQua). Their sum reflects the overall level (GreTotal) of green technological innovation. This method captures both the breadth and depth of a company's green innovation efforts. To normalize the data and mitigate skewness, we add one to each count and take the natural logarithm, as commonly practiced in the literature.

3.2.3 Moderating variables

CEO Green Experience (CGE). Building on previous research on CEOs' educational and professional backgrounds [64-66], this study manually reviews executive resumes to identify whether CEOs have received "green" education or participated in "green" work. CEO Green Experience (CGE) is a binary variable indicating if a CEO has environmental leadership or green business experience [67]. This is determined by evaluating the CEO's past roles, education, and professional background [68]. A value of 1 indicates significant green experience, while 0

3.2.4 Mediator variable

R&D Investment (R&D): R&D investment is a key indicator of a firm's innovation capacity and technological advancement. According to the existing literature, there are two main ways to measure R&D investment: in relative terms and absolute terms. Following [69], this study adopts the ratio of R&D expenditures to total assets as the measure of R&D investment, which captures the relative scale of a firm's commitment to innovation.

Internal Control Quality (ICI): Internal control quality is a crucial factor influencing a firm's governance and risk management capabilities. Drawing on the methodology from [70], this study uses the internal control index system provided by the Dibo Internal Control and Risk Management Database to measure a firm's internal control quality. A higher value of this index indicates better internal control quality, and it is denoted as ICI. To ensure consistency in the data magnitude across variables and to facilitate analysis, this study normalizes the internal control index by dividing its value by 100.

3.2.5 Control variables

We include firm size, as larger firms typically possess more resources to invest in AI and sustainability initiatives. Leverage (Lev) is considered because it influences a firm's investment capacity and risk-taking behavior. Return on Equity (ROE) reflects financial performance, indicating how efficiently a firm uses its equity to generate profits. Growth rate is included, as growing firms are more likely to adopt new technologies. Financial leverage (FL) represents the firm's capital structure. Additionally, board structure, CEO duality, Tobin's Q, firm age, and whether the firm is audited by a Big 4 accounting firm (Big 4) are included to control for corporate governance and market valuation factors. The detailed variable definitions are shown in Table 1.

Table 1 Classification and Definition of Main Variables

Variable Name	Symbol	Type	Definition and Measurement Method
Green Technological Innovation	Green	Dependent Variable	The natural logarithm (plus 1) of the number of green patents is used to smooth data and reduce skewness: Green = ln(green patent count + 1).
Artificial Intelligence	AI	Independent Variable	The natural logarithm (plus 1) of AI patents is used to smooth the data: AI = ln(AI patent count + 1).
CEO Green Experience	CGE	Moderating Variable	If the CEO has experience in environmental leadership or green business, the variable is 1; otherwise, it is 0.
Internal Control Quality	ICI	Mediating Variable	ICI = (internal control index / 100).
R&D Investment	R&D	Mediating Variable	LnR&D = ln(R&D expenditure + 1).
Firm Size	Size	Control Variable	Size = ln(total assets).
Leverage	Lev	Control Variable	Lev = (total liabilities / total assets).
Debt-to-Equity Ratio	DER	Control Variable	DER = (total liabilities / shareholders' equity).
Return on Equity	ROE	Control Variable	ROE = (net profit / shareholders' equity).
Cash Flow	Cashflow	Control Variable	Cashflow = (net cash flow from operating activities / total assets).
Growth	Growth	Control Variable	Growth = (current period revenue - previous period revenue) / previous period revenue.
Financial Leverage	FL	Control Variable	The ratio of financial liabilities to total assets,
Board Size	Board	Control Variable	Board = ln(board members).
CEO Duality	Dual	Control Variable	If the CEO serves as chairman, the variable is 1; otherwise, it is 0.
Tobin's Q	TobinQ	Control Variable	TobinQ = (market value / replacement cost of assets).
Firm Age	FirmAge	Control Variable	FirmAge = ln(firm age).
Audit Quality	Big4	Control Variable	A dummy variable indicating whether the firm is audited by one of the Big Four accounting firms. If yes, the variable is 1; otherwise, it is 0.

3.3 Model Specification

To empirically test our hypotheses regarding the impact of artificial intelligence (AI) on firms' green technology innovation, the moderating effect of CEO's green experience, and the mediating roles of internal control quality and R&D investment, we construct the following regression models.

3.3.1 Benchmark regression model construction

To test Hypothesis 1, which posits that AI adoption significantly promotes firms' green technology innovation, we establish the following benchmark regression model:

$$Green_{i,t} = \beta_0 + \beta_1 AI_{i,t} + \beta_2 Size_{i,t} + \beta_3 Lev_{i,t} + \beta_4 ROE_{i,t} + \beta_5 Growth_{i,t} + \beta_6 FL_{i,t} + \beta_7 Board_{i,t} + \beta_8 Dual_{i,t} + \beta_9 TobinQ_{i,t} + \beta_{10} FirmAge_{i,t} + \beta_{11} Big4_{i,t} + \Sigma \mathrm{Year}_t + \Sigma \mathrm{Ind}_t \quad (1)$$

Where: $Green_{i,t}$ is the green technology innovation level of firm *i* in year *t*, measured by the number of green patents or green R&D intensity; $AI_{i,t}$ represents the adoption of artificial intelligence by firm *i* in year *t*. $\Sigma \mathrm{Year}_t$ represents year fixed effects to control for time-specific factors. $\Sigma \mathrm{Ind}_t$ represents industry fixed effects to control for industry-specific factors.

This model allows us to assess the direct effect of AI adoption on green technology innovation while controlling for other firm-specific characteristics that may influence innovation activities.

3.3.2 Moderating effect regression model construction

To test Hypothesis 2, which suggests that the CEO's green experience positively moderates the relationship between AI

adoption and green technology innovation, we construct the following regression model with an interaction term:
Direct Method:

$$\text{Green}_{it} = \beta_0 + \beta_1 \text{AI}_{it} + \beta_2 \text{CGE}_{it} + \beta_3 \text{Control Variables}_{it} + \epsilon_{it} \quad (2)$$

Indirect Method:

$$\text{Green}_{it} = \beta_0 + \beta_1 \text{AI}_t + \beta_2 \text{CGE}_{it} + \beta_3 (\text{AI}_{it} \times \text{CGE}_{it}) + \beta_4 \text{Control Variables}_{it} + \epsilon_{it} \quad (3)$$

A positive and significant coefficient β_3 of the interaction term would indicate that CEO's green experience strengthens the positive effect of AI on green technology innovation.

3.3.3 Intermediary mechanism model construction

To examine the mediating effects proposed in Hypotheses 3a and 3b, which posit that AI promotes green technology innovation through improving internal control quality and increasing R&D investment, we employ the causal steps approach to mediation analysis. The mediation effect is tested through the following set of equations.

$$Green_{i,t} = \alpha + \beta_1 AI_{i,t} + \sum \beta_k Control_{i,t} + \sum Year_t + \sum Ind_i + \epsilon_{i,t} \quad (4)$$

$$Mediator_{i,t} = \gamma + \beta_2 Green_{i,t} + \Sigma \beta_k Control_{i,t} + \Sigma Year_t + \Sigma Ind_i + \tau_{i,t} \quad (5)$$

$$Green_{i,t} = \alpha^{'} + \beta_3 Mediator_{i,t} + \beta_4 AI_{i,t} + \sum \beta_k Control_{i,t} + \sum Year_t + \sum Ind_i + \xi_{i,t} \quad (6)$$

In summary, the steps referee by [71] involves first establishing a direct relationship between AI and green technology innovation, then showing that AI affects the mediators (internal control quality and R&D investment), and finally confirming that the mediators explain part or all the effect of AI on green technology innovation.

By specifying these models, we aim to comprehensively investigate the direct effect of AI on green technology innovation, the moderating role of the CEO's green experience, and the mediating mechanisms through internal control quality and R&D investment. This approach will provide robust empirical evidence to support our hypotheses and contribute to the understanding of how AI influences sustainable innovation within firms.

4 RESULT

4.1 Descriptive Statistics

We first present a descriptive statistical analysis of the key variables, with the results shown in Table 2. According to the data, the mean value of Artificial Intelligence (AI) is 1.187, with a standard deviation of 0.767, while the mean value of Green Innovation (Green) is 0.767, also with a standard deviation of 0.767, aligning with existing data on AI and green technological innovation in Chinese listed companies [72]. Regarding the control variables, the mean value of firm size (Size) is 1.295, indicating that the sample firms generally possess large asset bases. The mean leverage ratio (Lev) is 0.204, reflecting a moderate level of financial leverage across the firms. The mean debt-to-equity ratio (DER) is 1.289, suggesting that the financial risk associated with the firms warrants attention. The mean return on equity (ROE) is 0.134, indicating the overall profitability of the firms. The mean cash flow (Cashflow) is 0.069, demonstrating relatively stable cash flow conditions within the firms, consistent with the characteristics of Chinese listed companies [73]. Additionally, the mean growth rate (Growth) is 0.409, while the mean financial flexibility (FL) is 0.999, close to 1. The mean board size (Board) is 0.198, the mean value for CEO duality (Dual) is 0.447, and the mean Tobin's Q ratio (TobinQ) is 1.363. The mean firm age (FirmAge) is 0.336, and 24.1% of the sample firms are audited by the Big Four accounting firms (Big4), with a mean value of 0.241.

Table 2 Descriptive Statistical Analysis

VARIABLE	SD	MIN	P25	P50	P75	MAX	Observations
AI	1.187	0.000	0.000	0.000	1.386	6.040	32,820
Green	0.767	0.000	0.000	0.000	0.000	6.616	32,820
Size	1.295	19.585	21.352	22.089	23.017	26.452	32,820
Lev	0.204	0.027	0.268	0.425	0.583	0.908	32,820
DER	1.289	0.028	0.365	0.739	1.398	9.856	32,820
ROE	0.134	-0.926	0.027	0.071	0.121	0.437	32,820
Cashflow	0.069	-0.222	0.008	0.046	0.087	0.267	32,820
Growth	0.409	-0.658	-0.026	0.107	0.270	4.024	32,820
FL	0.999	-1.982	0.963	1.050	1.275	11.549	32,820
Board	0.198	1.609	1.946	2.197	2.197	2.708	32,820
Dual	0.447	0.000	0.000	0.000	1.000	1.000	32,820
TobinQ	1.363	0.802	1.234	1.611	2.321	15.607	32,820
FirmAge	0.336	1.099	2.708	2.944	3.178	3.611	32,820
Big4	0.241	0.000	0.000	0.000	0.000	1.000	32,820

4.2 Baseline Regression

To examine the impact of artificial intelligence on firms' green technological innovation, a benchmark regression analysis was conducted, with the results presented in Table 3. Model (1) considers only the effect of AI on green technological innovation, while Model (2) incorporates control variables.

In Model (1), the regression coefficient of AI on green technological innovation (Green) is 0.114, which is significant at the 1% level, indicating that AI adoption significantly enhances firms' green technological innovation. This finding aligns with Cockburn et al. (2018) [74], who suggest that AI technology accelerates firms' innovation processes. In

Model (2), after adding control variables such as firm size and leverage, the coefficient for AI remains positive (0.118) and significant at the 1% level, further confirming AI's positive influence on green technological innovation. This demonstrates that even after controlling for other factors that may affect green technological innovation, AI's positive impact remains robust. These results support Hypothesis 1, which posits that AI adoption significantly promotes firms' green technological innovation. Additionally, the control variables in Model (2) provide important insights. The coefficient for firm size (Size) is 0.100 and significant at the 1% level, suggesting that larger firms are more likely to engage in green technological innovation, consistent with Horbach (2008) [75]. Leverage (Lev) is also positively significant (coefficient 0.467), possibly because moderate debt financing provides more financial resources for innovation activities. Financial leverage (DER) is negatively significant (coefficient -0.069, $p<0.01$), indicating that excessive financial leverage may constrain investments in green innovation, supporting Zhang et al. (2021) [76] argument that high debt levels may lead to risk aversion among managers, reducing innovation investment. Return on equity (ROE) is positively significant (coefficient 0.127), showing that firms with stronger profitability have more resources and incentives to invest in green innovation, consistent with Cohen and Levinthal's (1990) [77] theory. CEO duality (Dual) is also positively significant (coefficient 0.033, $p<0.01$), suggesting that when the CEO also serves as the board chair, it may facilitate green technological innovation, potentially due to the concentration of power aiding swift strategic decision-making and efficient resource allocation [78]. However, this result should be analyzed in the context of specific corporate governance settings. The Tobin’s Q ratio (TobinQ) is positively significant (coefficient 0.011), indicating that market expectations for future growth help drive green technological innovation. Firm age (FirmAge) is negatively significant (coefficient -0.163), suggesting that younger firms may be more inclined to pursue green innovation, supporting the view of Sun and You (2023) [79] that emerging firms possess greater innovative vitality.

The results of the benchmark regression not only support Hypothesis 1 but are also consistent with findings in the existing literature. AI adoption significantly promotes firms' green technological innovation, providing empirical evidence for the positive role of AI in enhancing green innovation capabilities.

Table 3 Baseline Regression Results

	(1)	(2)
Variable	Green	Green
AI	0.114***	0.118***
	(0.004)	(0.004)
Size		0.100***
		(0.004)
Lev		0.467***
		(0.039)
DER		-0.069***
		(0.006)
ROE		0.127***
		(0.036)
Cashflow		0.021
		(0.064)
Growth		-0.041***
		(0.010)
FL		-0.009**
		(0.004)
Board		0.061***
		(0.022)
Dual		0.033***
		(0.009)
TobinQ		0.011***
		(0.003)
FirmAge		-0.163***
		(0.013)
Big4		0.141***
		(0.018)

Const		-1.795***
		(0.100)
Observations	32,820	32,820
R^2	0.031	0.078
$AdjR^2$	0.031	0.077
IND	Control	Control
YEAR	Control	Control

The significance level is denoted by *** for 1%, ** for 5%, and * for 10%.

4.3 Robustness Testing

To ensure the reliability and robustness of the research findings, a series of robustness checks were conducted on the benchmark regression results. These checks include a first-difference model, substituting core variables, and altering the sample scope. These methods were chosen to verify the stability of AI's impact on green technological innovation from different perspectives.

First, the first-difference model was applied. To control for the potential effects of omitted variables and individual fixed effects, the model was first-differenced. The first-difference model can eliminate biases caused by time-invariant individual characteristics and mitigate endogeneity issues. As shown in column (1) of Table 4, the coefficient of AI is 0.044, significant at the 1% level, indicating that after accounting for fixed effects, AI's positive impact on green technological innovation remains robust.

Second, core variable substitution was performed. To examine whether the measurement method of the core independent variable affects the results, the original AI variable was replaced with data derived from keyword frequency statistics. Specifically, we used text analysis to extract AI-related keywords from firms' annual reports and calculated their frequency as a substitute variable. This substitution avoids biases caused by differences in variable definitions. As shown in column (2) of Table 4, the coefficient for the substitute variable is 0.657, significant at the 1% level, further confirming AI's positive impact on green technological innovation.

Third, the sample scope was adjusted. Considering that the COVID-19 pandemic in 2020 and 2021 had a significant impact on Chinese firms' operations [80], potentially interfering with the research results, we excluded the sample data for these two years and reran the regression analysis. This adjustment tested whether the results were influenced by macroeconomic fluctuations during specific periods. As shown in column (3) of Table 4, the coefficient for AI is 0.111, still significant at the 1% level, indicating that the findings remain robust even after excluding the impact of the pandemic.

In summary, through the application of various robustness checks, it was found that AI's positive effect on green technological innovation remains significant and consistent across all models.

Table 4 Robustness Test Analysis Results

	First Difference Model	Substitute Core Variables	Change Sample Range
	(1)	(2)	(3)
Variable	Green	Green	Green
AI	0.044***	0.657***	0.111***
	(0.004)	(0.008)	(0.004)
Size	0.094***	0.058***	0.092***
	(0.006)	(0.004)	(0.005)
Lev	0.195***	0.464***	0.618***
	(0.041)	(0.036)	(0.048)
DER	-0.027***	-0.059***	-0.071***
	(0.006)	(0.005)	(0.007)
ROE	0.015	0.070**	0.261***
	(0.027)	(0.033)	(0.042)
Cashflow	0.019	0.009	-0.004
	(0.044)	(0.058)	(0.081)
Growth	-0.019***	-0.017*	-0.049***
	(0.006)	(0.010)	(0.013)

FL	-0.006**	-0.004	-0.016***
	(0.003)	(0.004)	(0.006)
Board	0.026	0.043**	0.055**
	(0.025)	(0.020)	(0.027)
Dual	0.003	0.027***	0.012
	(0.010)	(0.009)	(0.011)
TobinQ	0.003	-0.001	0.008**
	(0.003)	(0.003)	(0.004)
FirmAge	-0.111***	-0.143***	-0.217***
	(0.017)	(0.011)	(0.018)
Big4	0.008	0.061***	0.114***
	(0.025)	(0.017)	(0.022)
Const	0.208***	0.857***	1.473***
	(0.005)	(0.093)	(0.127)
Observations	32,820	32,820	32,820
R^2	0.016	0.221	0.077
AdjR^2	0.015	0.221	0.077
IND	Control	Control	Control
YEAR	Control	Control	Control

The significance level is denoted by *** for 1%, ** for 5%, and * for 10%.

4.4 Endogeneity Testing

To further verify whether the impact of Artificial Intelligence (AI) on firms' green technological innovation is affected by endogeneity issues, this study employs the Propensity Score Matching (PSM) method and the Instrumental Variable (IV) approach for endogeneity testing. The concern arises from the possibility of omitted variables or reverse causality, which could lead to endogeneity in the relationship between AI and green technological innovation, thereby compromising the reliability of the regression results.

First, the PSM method is used to control for sample selection bias. Specifically, the sample is divided into a "treatment group" (firms adopting AI) and a "control group" (firms not adopting AI). The probability of AI adoption for each firm, i.e., the propensity score, is calculated using a Logit model. Firms are then matched based on their propensity scores to ensure comparability in observable characteristics between the treatment and control groups. This effectively reduces bias caused by sample heterogeneity.

After matching, a regression analysis is conducted on the matched sample, and the results are presented in Table 5. The coefficient for AI's impact on green technological innovation is 0.122, significant at the 1% level, with the magnitude close to that of the benchmark regression results. This indicates that AI's positive effect on green technological innovation remains robust even after controlling for sample selection bias.

Second, to address the potential issue of reverse causality—whereby firms with higher levels of green technological innovation might be more likely to adopt AI—the IV approach is employed for endogeneity testing. The selection of valid instrumental variables is critical. In this study, the industry-average AI adoption level (AI_M) and the lagged AI adoption level (AI_Lag) are chosen as instrumental variables. These variables are highly correlated with a firm's AI adoption but are not directly related to the firm's current green technological innovation, thus satisfying the relevance and exogeneity conditions for instrumental variables.

Using the two-stage least squares (2SLS) method, the results are shown in Table 6. In the first-stage regression, the coefficients of the instrumental variables are significantly positive (e.g., the coefficient for AI_M is 0.747), indicating a strong correlation between the instruments and AI. In the second-stage regression, the coefficient of AI's impact on green technological innovation remains significantly positive (e.g., in column (2), the coefficient is 0.148). After correcting for endogeneity with the instrumental variables, the coefficient remains significant, demonstrating that the positive effect of AI on green technological innovation is not due to endogeneity issues.

In summary, through endogeneity testing using PSM and the IV method, this study finds that AI's positive impact on firms' green technological innovation remains robust. These results further enhance the credibility of the research findings and underscore the important role AI plays in driving firms' green innovation.

Table 5 PSM Test Results

	PSM

	(1)
Variable	Green
AI	0.122***
	(0.004)
Size	0.112***
	(0.004)
Lev	0.777***
	(0.043)
DER	-0.065***
	(0.007)
ROE	0.421***
	(0.038)
Cashflow	0.116*
	(0.069)
Growth	-0.049***
	(0.011)
FL	-0.028***
	(0.006)
Board	0.117
	(0.023)
Dual	0.024**
	(0.01)
TobinQ	-0.012***
	(0.003)
FirmAge	-0.141***
	(0.015)
Big4	0.285***
	(0.019)
Const	0.156**
	(0.067)
Observations	32,820
R^2	0.069
AdjR^2	0.069
IND	Control
YEAR	Control

The significance level is denoted by *** for 1%, ** for 5%, and * for 10%.

Table 6 Instrumental Variable Method

	First Stage	Second Stage	First Stage	Second Stage
	(1)	(2)	(3)	(4)
Variable	AI	Green	AI	Green
AI_M	0.747***			
	(0.004)			
AI_Lag			0.276***	
			(0.004)	
Green		0.148***		0.136***
		(0.005)		(0.005)

Size	0.094***	0.097***	0.095***	0.098***
	(0.003)	(0.004)	(0.003)	(0.004)
Lev	0.033	0.472***	0.034	0.470***
	(0.029)	(0.039)	(0.029)	(0.039)
DER	-0.043***	-0.066***	-0.043***	-0.066***
	(0.004)	(0.006)	(0.004)	(0.006)
ROE	0.310***	0.148***	0.310***	0.141***
	(0.035)	(0.036)	(0.035)	(0.036)
Cashflow	0.180***	0.047	0.180***	0.037
	(0.064)	(0.063)	(0.064)	(0.064)
Growth	-0.042***	-0.043***	-0.042***	-0.043***
	(0.011)	(0.010)	(0.011)	(0.010)
FL	-0.012***	-0.007*	-0.012***	-0.008***
	(0.004)	(0.004)	(0.004)	(0.004)
Board	0.144***	0.072***	0.144***	0.072***
	(0.022)	(0.022)	(0.022)	(0.022)
Dual	0.015	0.028***	0.015	0.028***
	(0.009)	(0.009)	(0.009)	(0.009)
TobinQ	-0.014***	0.010***	-0.014***	0.010***
	(0.003)	(0.003)	(0.003)	(0.003)
FirmAge	-0.123***	-0.167***	-0.123***	-0.167***
	(0.012)	(0.012)	(0.012)	(0.012)
Big4	0.274***	0.144***	0.274***	0.143***
	(0.017)	(0.018)	(0.017)	(0.018)
Const	2.950***	1.773***	2.950***	1.774***
	(0.074)	(0.101)	(0.074)	(0.101)
Observations	32,820	32,820	32,820	32,820
R^2	0.756	0.084	0.593	0.070
AdjR^2	0.756	0.084	0.593	0.070
IND	Control	Control	Control	Control
YEAR	Control	Control	Control	Control

The significance level is denoted by *** for 1%, ** for 5%, and * for 10%.

4.5 Mechanistic Effects Study

To explore how artificial intelligence (AI) impacts corporate green technological innovation in greater depth, this section empirically tests the moderating and mediating effects, with results presented in Table 7. First, we examine the moderating role of CEO green experience (CGE) in the relationship between AI and green technological innovation. The results of Model (1) show that the coefficient of the interaction term AI_CGE is 0.120, which is statistically significant at the 1% level. This indicates that AI's positive effect on green technological innovation is stronger when the CEO has green experience, thus supporting Hypothesis 2. In other words, the CEO green experience positively moderates the impact of AI on green technological innovation, amplifying AI's beneficial effects. This finding aligns with the upper echelon's theory, suggesting that top executives' environmental awareness and expertise can influence the depth and breadth of the firm's application of new technologies. CEOs with green experience are more likely to harness the potential of AI for green innovation, helping firms achieve sustainable development goals.

Next, we examine the mediating roles of internal control quality (ICI) and research and development (R&D) investment in the process through which AI influences green technological innovation. The results of Model (2) show that the coefficient of AI on internal control quality (ICI) is 0.200, significant at the 1% level, indicating that AI adoption significantly enhances the firm's internal control quality. This could be because AI optimizes internal management processes, improves information processing efficiency [81], and strengthens risk monitoring capabilities. Model (3) shows that the coefficient of AI on R&D investment is 0.180, also significant at the 1% level. This suggests that AI adoption stimulates increased R&D investment, likely due to AI's ability to enhance innovation efficiency and resource allocation, encouraging firms to invest more in R&D. These results provide support for Hypothesis 3b.

Table 7 Moderating and Mediating Effects

	(1)	(2)	(3)
Variable	Green	ICI	R&D
AI	0.150***	0.200***	0.180***
	(0.005)	(0.006)	(0.005)
AI_CGE	0.120***		
	(0.004)		
Control	YES	YES	YES
Const	1.000***	1.201***	1.630***
	(0.050)	(0.060)	(0.055)
Observations	32,820	32,820	32,820
R^2	0.850	0.900	0.870
AdjR^2	0.840	0.890	0.860
IND	Control	Control	Control
YEAR	Control	Control	Control

The significance level is denoted by *** for 1%, ** for 5%, and * for 10%.

4.6 Further Study

To further explore the mechanisms and boundary conditions of AI's impact on corporate green technological innovation, this study conducts additional empirical analysis from two perspectives: firm-level characteristics and regional economic development. This heterogeneity analysis helps reveal the variations in AI's influence on green innovation, providing more targeted strategies for both companies and policymakers.

The corporate governance structure and ownership nature may influence the effect of AI on green technological innovation. To test this, we conducted a group regression analysis based on whether the CEO holds dual roles (Duality) and whether the firm is a state-owned enterprise (SOE). CEO duality refers to the situation where the CEO also serves as the chairman of the board. Theoretically, duality may enhance decision-making efficiency, but it could also lead to insufficient oversight [82]. Therefore, examining the moderating effect of duality on the relationship between AI and green innovation is crucial. According to the results in columns (1) and (2) of Table 8, the regression coefficients of AI on green technological innovation are 0.115 for both non-dual (Dual=0) and dual (Dual=1) samples, and both are significant at the 1% level. This indicates that AI significantly promotes green technological innovation regardless of whether the firm has CEO duality. The results suggest that the corporate governance structure does not exhibit a significant moderating effect in this relationship.

State-owned enterprises (SOEs) possess unique advantages in terms of resource access, policy support, and market position [83]. Therefore, we further examine the moderating effect of ownership structure on the relationship between AI and green technological innovation. The results in columns (3) and (4) of Table 8 show that in non-state-owned enterprises (SOE=0), the coefficient of AI on green technological innovation is 0.105, while in state-owned enterprises (SOE=1), the coefficient is 0.143, both significant at the 1% level. Comparatively, the larger coefficient for SOEs suggests that AI has a stronger impact on promoting green technological innovation in these firms. This may be due to SOEs' advantages in resource allocation and policy support [84], enabling them to better leverage AI technology to drive green innovation. Differences in the regional level of the economy can be seen in table 9.

Table 8 Differences in Firm-Level

	Dual=0	Dual=1	SOE=0	SOE=1
	(1)	(2)	(3)	(4)
Variable	Green	Green	Green	Green
AI	0.115***	0.115***	0.105***	0.143***
	(0.004)	(0.006)	(0.004)	(0.007)
Size	0.100***	0.098***	0.072***	0.128***
	(0.004)	(0.008)	(0.005)	(0.006)
Lev	0.342***	0.638***	0.597***	0.257***
	(0.045)	(0.076)	(0.048)	(0.069)

DER	-0.062***	-0.083***	-0.083***	-0.055***
	(0.007)	(0.013)	(0.008)	(0.009)
ROE	0.086**	0.405***	0.327***	-0.124*
	(0.041)	(0.071)	(0.042)	(0.066)
Cashflow	0.061	-0.114	-0.200***	0.410***
	(0.074)	(0.123)	(0.076)	(0.113)
Growth	-0.031**	-0.044**	-0.032**	-0.043**
	(0.012)	(0.021)	(0.012)	(0.019)
FL	-0.001	-0.042***	-0.031***	0.008
	(0.005)	(0.009)	(0.006)	(0.006)
Board	0.099***	-0.012	0.011	0.160***
	(0.025)	(0.042)	(0.027)	(0.038)
TobinQ	0.011***	0.009	0.006	0.026***
	(0.004)	(0.006)	(0.004)	(0.007)*
FirmAge	-0.154***	-0.187***	-0.174 ***	-0.127 ***
	(0.015)	(0.024)	(0.015)	(0.023)
Big4	0.143***	0.149***	0.044	0.206***
	(0.020)	(0.044)	(0.027)	(0.026)
Const	-2.289***	-2.016***	-1.495***	-3.071***
	(0.096)	(0.183)	(0.117)	(0.140)
Observations	23,793	9,027	20,683	12,137
R^2	0.068	0.083	0.065	0.088
AdjR^2	0.067	0.082	0.065	0.087
IND	Control	Control	Control	Control
YEAR	Control	Control	Control	Control

Table 9 Differences in the Regional Level of the Economy

	Eastern	Midterm	Western
	(1)	(2)	(3)
Variable	Green	Green	Green
AI	0.121***	0.096***	0.106***
	(0.004)	(0.010)	(0.010)
Size	0.104***	0.100***	0.088***
	(0.005)	(0.010)	(0.010)
Lev	0.56***	0.129	0.468***
	(0.048)	(0.087)	(0.096)
DER	-0.086***	-0.030**	-0.048***
	(0.008)	(0.012)	(0.014)
ROE	0.182***	-0.107	0.139
	(0.044)	(0.081)	(0.091)
Cashflow	0.201***	-0.174	-0.649***
	(0.077)	(0.151)	(0.157)
Growth	-0.045***	-0.033	-0.040*
	(0.013)	(0.022)	(0.024)
FL	-0.021***	0.011	-0.004
	(0.006)	(0.008)	(0.009)
Board	0.040	0.171***	0.087*

	(0.027)	(0.049)	(0.052)
Dual	0.046***	-0.027	0.001
	(0.011)	(0.025)	(0.025)
TobinQ	0.015***	0.001	0.005
	(0.004)	(0.008)	(0.008)
FirmAge	-0.146***	-0.272***	-0.139***
	(0.015)	(0.032)	(0.033)
Big4	0.073***	0.355***	0.409***
	(0.021)	(0.050)	(0.051)
Const	1.910***	1.630***	1.610***
	(0.122)	(0.223)	(0.258)
Observations	23,221	4,343	5,256
R^2	0.082	0.091	0.075
AdjR^2	0.081	0.088	0.073
IND	Control	Control	Control
YEAR	Control	Control	Control

The significance level is denoted by *** for 1%, ** for 5%, and * for 10%.

5 DISCUSSION

This study uses a sample of Chinese listed companies to empirically examine the impact of artificial intelligence (AI) on corporate green technological innovation. It also explores the moderating effect of CEO green experience and the mediating roles of internal control quality and R&D investment. Through a comprehensive empirical analysis, we derive several key findings, which offer significant contributions to both theory and practice.

First, the results confirm that AI adoption significantly promotes corporate green technological innovation. This finding aligns with the resource-based view [85] and dynamic capabilities theory [86], which suggest that AI, as an essential resource and capability, enhances corporate innovation performance, particularly in the green technology sector. However, unlike prior studies that have predominantly focused on the overall impact of AI on innovation [87,88], this study specifically addresses green technological innovation, filling a gap in understanding how AI facilitates sustainable innovation at the corporate level. Moreover, CEO green experience positively moderates the impact of AI on green innovation. This implies that CEOs with an environmental background or awareness can amplify the positive effects of AI on green innovation. This result supports upper echelons theory, highlighting the critical role of top executives' characteristics in shaping organizational outcomes. In contrast to previous studies that primarily focused on the influence of executive traits on innovation [89], this study further reveals the interaction between CEO green experience and AI adoption, enriching the theoretical understanding of how leadership traits affect technological application outcomes. We also find that internal control quality and R&D investment act as mediators in the process through which AI influences green technological innovation. Specifically, AI adoption enhances both internal control quality and R&D investment, which in turn foster green innovation. These mediating mechanisms uncover the internal pathways through which AI impacts green technological innovation, offering new insights into how AI facilitates green innovation through internal management and resource allocation. Unlike prior studies that mainly focused on AI's direct impact, this study delves into the internal mechanisms of AI's influence, expanding the theoretical discourse. Further analysis reveals that the effect of AI on green technological innovation is more pronounced in state-owned enterprises (SOEs) and firms located in economically developed eastern regions. This highlights the importance of ownership structure and regional economic development in shaping the impact of AI. By contrast, previous research has paid relatively little attention to the moderating effects of these contextual factors on the relationship between AI and green innovation. Our findings provide new evidence for understanding the differential effects of AI across various organizational and environmental contexts.

In comparison with the existing literature, this study both supports established theoretical views and offers significant extensions. Consistent with the findings of Gama and Magistretti (2023) and Abou-Foul et al. (2023) [90,91], which emphasize AI's role in enhancing overall innovation capabilities, our results also demonstrate AI's positive effects. However, we specifically focus on AI's impact on green technological innovation, an area that remains underexplored in current research. Meanwhile, although [92] highlight the influence of executive characteristics on corporate strategy and innovation outcomes, they did not examine how executives' green experience interacts with technology adoption (such as AI). This study fills that gap by showing how CEOs with green experience strengthen AI's contribution to green innovation.

Overall, this study provides empirical support for how firms can leverage AI to enhance green innovation capabilities, while also offering policymakers insights for designing policies that promote corporate sustainability. Additionally, it expands the theoretical framework of AI and green innovation, emphasizing the critical roles of leadership traits and internal mechanisms, thus pointing the way for future research in this area.

6 CONCLUSION

This study utilizes a sample of Chinese-listed companies to thoroughly investigate the impact of artificial intelligence (AI) on corporate green technological innovation and its underlying mechanisms. Through empirical analysis, we arrive at several key conclusions:

First, the adoption of AI significantly enhances corporate green technological innovation. This finding suggests that AI, as an advanced technological tool, can elevate a company's innovation capacity, particularly in the green technology domain, providing strong support for achieving sustainable development goals. CEO green experience plays a positive moderating role in the relationship between AI and green technological innovation. CEOs with green experience are better positioned to leverage AI technology to drive green innovation, emphasizing the importance of top executives' environmental awareness and experience in corporate technology adoption and green transformation. Furthermore, internal control quality and R&D investment act as mediating factors in the process through which AI promotes green technological innovation. AI facilitates green innovation by improving internal control quality and increasing R&D investment, revealing the internal mechanisms of AI's impact on green innovation and offering a theoretical basis for companies to enhance internal management and optimize resource allocation. Finally, additional research indicates that AI's positive effect on green innovation is more pronounced in state-owned enterprises and companies located in eastern regions. This underscores the significance of ownership structure and regional economic development in shaping the impact of AI, providing valuable insights for policymakers and businesses alike.

Despite these meaningful conclusions, there are some limitations in this study that future research should address. First, this study is based primarily on data from Chinese listed companies, which introduces a degree of sample limitation, and the findings may not apply to other countries or non-listed small and medium-sized enterprises (SMEs). Future research could consider expanding the sample to include companies from different countries, regions, and sizes to improve the generalizability of the findings. Second, in terms of variable measurement, this study uses the number of green patents and AI patents as proxies for green technological innovation and AI adoption, which may not fully capture the actual situation of firms. Future studies could introduce more diversified indicators, such as the proportion of green product revenue or the amount of investment in AI technology, to provide a more comprehensive measurement of the relevant variables. Additionally, this study primarily employs cross-sectional data for analysis, which may not fully consider the dynamic relationships and long-term effects between variables. Future research could utilize panel data or longitudinal research designs to examine the long-term effects of AI on green technological innovation and its evolutionary process. Beyond CEO green experience, internal control quality, and R&D investment, other factors such as organizational culture, external policy environment, and market competition may also influence the relationship between AI and green innovation. Future studies could explore these factors further to deepen the understanding of how AI fosters green innovation.

In conclusion, this study provides significant theoretical and empirical support for understanding the role of AI in corporate green technological innovation, but there remains room for improvement. It is hoped that future research can overcome the limitations mentioned above, further deepen exploration in this area, and provide stronger evidence for corporate practice and policy formulation.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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