

Article

How Does Artificial Intelligence Shape Green Innovation Ambidexterity? The Moderating Role of Managerial Characteristics

Jing Lu ¹, Xixiang Sun ¹ and Wei Zhang ^{2,*}

¹ School of Management, Wuhan University of Technology, Wuhan 430070, China; lu_jing@whut.edu.cn (J.L.); 13971190718@163.com (X.S.)

² School of Safety Science and Emergency Management, Wuhan University of Technology, Wuhan 430070, China

* Correspondence: zhangweify@whut.edu.cn

Highlights

Please indicate how your work links to systems science via your contributions to systems practice, theory, and/or methodology.

- This study conceptualizes AI adoption, dynamic capabilities, and green innovation ambidexterity as interdependent components within a systemic framework and examines the nonlinear relationships among these variables.
- This study integrates organizational ambidexterity theory with dynamic capabilities theory to develop a systems-oriented framework explaining how AI adoption reshapes the balance between exploratory and exploitative green innovation.

What are the main findings and/or the implications of the main findings?

- AI adoption reshapes firms' dynamic capabilities and thereby exerts an inverted U-shaped effect on green innovation ambidexterity, such that moderate adoption fosters a balance between exploratory and exploitative green innovation, whereas excessive adoption disrupts this balance.
- CEO IT background and green experience weaken the inverted U-shaped relationship between AI adoption and green innovation ambidexterity, whereas CEO power attenuates the moderating effect of CEO IT background on this relationship.

Abstract

Amid the rapid advancement of artificial intelligence (AI) technology and growing environmental pressures, this study empirically examines the impact of AI adoption intensity on green innovation ambidexterity (GIA), drawing on organizational ambidexterity theory and dynamic capabilities theory. We also examine the complementary and moderating roles of CEO characteristics in the context of AI technology. Using data from Chinese A-share listed firms during 2011–2025, we test these hypotheses. The results show that AI adoption intensity exhibits an inverted U-shaped relationship with GIA. Mechanism analysis shows that dynamic capabilities mediate the relationship between AI adoption intensity and GIA. Both CEO IT background and CEO green experience attenuate the effect of AI adoption intensity on GIA. CEO power attenuates the moderating effect of CEO IT background on this relationship. Heterogeneity tests indicate that the effect of AI adoption intensity on GIA is more pronounced in non-heavy-polluting industries and state-owned enterprises. This study provides new evidence on the link between AI adoption and GIA. It also clarifies and validates the complementary and moderating effects of CEO characteristics on AI-driven outcomes, offering practical micro-level insights for firms to strategically deploy digital technologies and achieve sustainable and balanced green innovation.



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Keywords: green innovation ambidexterity; AI adoption; double-edged sword effects; dynamic capability; CEO characteristics

1. Introduction

The growing urgency of global environmental problems has positioned green innovation as a key pathway for firms to reconcile economic growth with environmental sustainability [1–3]. Currently, with the rapid development and widespread application of digital technology, artificial intelligence (AI) has become an important tool for firms seeking to improve their green innovation performance [4,5]. Existing studies have shown that AI can significantly promote green innovation [6,7]. However, prior research has largely focused on green innovation as a whole, paying relatively limited attention to green innovation ambidexterity (GIA) [8]. Drawing on organizational ambidexterity theory [9], ambidexterity refers to an organization's ability to dynamically balance exploration and exploitation [10]. Accordingly, GIA captures firms' capacity to balance exploratory and exploitative green innovation. Exploratory green innovation involves the development of novel or disruptive green technologies, products, and processes through the acquisition and application of new knowledge, whereas exploitative green innovation emphasizes the refinement, improvement, and upgrading of existing green technologies, products, and processes [11]. By enabling firms to simultaneously pursue innovation novelty and efficiency, GIA is critical to long-term sustainable development [12]. Nevertheless, because exploratory and exploitative green innovation often compete for limited organizational resources, incumbent firms may find it difficult to achieve an effective balance between the two [13]. Therefore, identifying the key antecedents that enable firms to develop and sustain GIA remains an important research issue [14].

Although GIA is critical to firms' long-term development, existing studies have primarily examined the enabling effects of AI and other digital technologies on exploratory and exploitative green innovation separately [11,15]. In other words, prior research has largely focused on the outcomes of individual dimensions of green innovation, while paying insufficient attention to how AI adoption intensity affects firms' ability to balance exploratory and exploitative green innovation. Yet, maintaining such a balance is essential for sustaining long-term competitiveness and sustainable development [12]. Therefore, examining the impact of AI adoption intensity on GIA is warranted.

Drawing on organizational ambidexterity theory [9] and dynamic capabilities theory [16], this study investigates the relationship between AI adoption intensity and GIA. Organizational ambidexterity theory suggests that firms must effectively balance exploratory and exploitative green innovation to sustain competitive advantage, while the achievement of such a balance depends critically on firms' dynamic capabilities [17]. On the one hand, AI adoption can reduce information acquisition costs, improve the efficiency of green R&D decision-making, optimize resource allocation, and strengthen firms' abilities to sense and seize opportunities and reconfigure resources. These improvements in dynamic capabilities can facilitate the coordination of exploratory and exploitative green innovation, thereby enhancing GIA. On the other hand, excessive AI adoption may generate information overload, reinforce technological and organizational path dependence, and create imbalances across organizational functions. These adverse effects may weaken firms' dynamic capabilities and, in turn, impede the effective balance between exploratory and exploitative green innovation. Thus, these competing mechanisms suggest that the effect of AI adoption intensity on GIA may vary across different levels of AI adoption rather than follow a simple

linear pattern. This raises the possibility of a nonlinear relationship between AI adoption intensity and GIA, which warrants further theoretical and empirical investigation.

In addition, human judgment and managerial cognition remain fundamental to green innovation [18]. This study therefore argues that CEO characteristics constitute important boundaries for the relationship between AI adoption intensity and GIA. As the primary decision-maker responsible for firms' strategy, the CEO plays a central role in technology adoption and green R&D activities and can substantially shape firms' dynamic capabilities [19–21]. Accordingly, this study focuses on two CEO characteristics: IT background and green experience. CEO IT background refers to whether a CEO's educational or professional background is related to information technology or closely related fields [22,23], whereas CEO green experience refers to whether a CEO's educational or professional experience is associated with environmental protection, green development, or related domains [24]. Both types of experience can reshape CEOs' knowledge structures, enhance their ability to interpret technological or environmental information, and reduce firms' dependence on AI-generated information and capabilities. As a result, they may attenuate the effect of AI adoption intensity on GIA.

This study further examines the moderating role of CEO power in shaping these boundary effects. CEO power refers to the extent to which a CEO is able to influence a major firm's decisions [25]. Greater CEO power increases the extent to which a CEO's knowledge, experience, and cognitive preferences are embedded in strategic decision-making. Therefore, CEO power may alter the extent to which CEO IT background and green experience shape the relationship between AI adoption intensity and GIA. By introducing CEO power as a higher-order boundary condition, this study provides a more nuanced understanding of when and how managerial characteristics influence the organizational consequences of AI adoption.

This study makes three main theoretical contributions to the literature on AI and innovation. First, drawing on organizational ambidexterity theory [9], we shift the focus from the separate effects of AI on exploratory and exploitative green innovation to its influence on the balance between the two. Existing studies have largely investigated how AI affects individual dimensions of green innovation independently. By examining GIA as a distinct organizational outcome, this study extends research on AI-enabled green innovation from a single-dimensional perspective to an ambidexterity perspective and enriches understanding of how firms can simultaneously pursue novelty and efficiency in green innovation. Second, drawing on dynamic capabilities theory [16], this study develops a capability-based explanation for how AI adoption intensity influences GIA. Rather than treating AI merely as a technological input, we conceptualize its organizational effects through changes in firms' dynamic capabilities. Specifically, we construct a comprehensive dynamic capabilities index encompassing opportunity sensing, opportunity seizing, and resource allocation and integration, and empirically demonstrate that AI adoption reshapes these capabilities, which in turn affect GIA. This extends the literature by clarifying the organizational capability mechanisms through which AI influences the balance between exploratory and exploitative green innovation. Third, this study identifies CEO characteristics as important boundary conditions of the AI adoption–GIA relationship, thereby extending research on the role of human capital and managerial characteristics in technology-enabled innovation. By examining CEO IT background and green experience, we show how managerial knowledge and experience can shape firms' reliance on and responses to AI technologies. Furthermore, by introducing CEO power as a higher-order moderator, we demonstrate that the influence of CEO characteristics on strategic outcomes depends not only on what CEOs know or have experienced, but also on the extent to which they are able to translate these characteristics into corporate decision-making [26].

This provides a more comprehensive perspective on the interplay among AI adoption, managerial characteristics, and organizational innovation.

2. Literature Review

2.1. Green Innovation Ambidexterity

Global climate initiatives, including the Paris Agreement, recognize technological innovation as a key component of the transition toward low-carbon development. In this international context, green innovation ambidexterity (GIA) emphasizes firms' simultaneous pursuit of exploratory and exploitative green innovation. Research on the determinants of green innovation has mainly drawn on institutional theory [27], the resource-based view [28], dynamic capabilities theory [29], and upper echelons theory [30]. These studies mainly focus on determinants at two levels: the external environment and firms' internal factors. However, a substantial body of empirical evidence indicates that the same determinant often exerts divergent effects on exploratory and exploitative green innovation.

From the perspective of external environmental factors, some studies drawing on institutional theory suggest that firms' green innovation is driven not only by internal factors but also by pressures from external environmental systems, market norms, and other forces [31]. Liu et al. [32] pointed out that policy tools such as environmental regulations and green subsidies can shape the costs and benefits of firms pursuing exploratory and exploitative green innovation, thereby exerting differential effects on the two. In the Chinese context in particular, the effectiveness of policy tools varies considerably. Strict environmental regulations can create compliance pressure on firms, compelling them to pursue exploitative green innovation—which typically involves lower risks and shorter return cycles—to meet short-term requirements, whereas incentive policies tend to promote exploratory green innovation [32]. At the same time, some studies have found that external institutions positively affect both types of green innovation [33]. In addition, stakeholder pressures—such as customers' green preferences, investors' expectations, and public environmental concerns—also constitute external sources of pressure that influence both types of green innovation [34].

However, the effects of external factors are often moderated by internal factors such as firm resources, technology, and executive characteristics. Therefore, internal factors also play an important role in shaping green innovation ambidexterity (GIA). The resource-based view posits that firms' green innovation depends on the heterogeneous green resources they possess [35,36]. Sufficient resources can simultaneously facilitate both types of green innovation activities. As research has advanced, a growing body of studies has found that dynamic capabilities play a more prominent role in shaping both types of green innovation [37]. This is because green innovation requires opportunity sensing to identify external green opportunities, opportunity seizing to mobilize resources for green R&D, and resource allocation and integration to distribute resources across the two types of green innovation [13]. In addition, continuous technological advances have provided new support for green innovation. Recently, a growing number of studies have focused on the effects of digital technologies, such as AI [38], on green innovation. Some studies have found that digital technology exerts a significant positive effect on GIA [39]. In addition, the executive team constitutes the micro-cognitive foundation of the firm, and its characteristics can also significantly affect both types of green innovation [40,41]. Accordingly, many studies treat executive characteristics as both an independent variable and a moderating variable in GIA research.

2.2. AI Adoption Intensity

As a core driving force behind the new wave of technological revolution, AI has made its adoption a focal point of scholarly research [5,42]. Currently, most studies treat AI adoption as an independent variable and examine its economic consequences. Although findings remain inconclusive, existing studies largely focus on the positive effects [43,44] and negative effects of AI [45].

First, most studies focus on the role of AI in enhancing corporate performance [46,47], innovation [48], and related outcomes. AI applications can significantly reduce firms' costs of acquiring, filtering, and analyzing information while expanding the scope of their knowledge search [49]. By leveraging AI technology, firms can promptly capture dispersed industry information, national policies, market signals, and other data, thereby gaining cross-disciplinary knowledge that would otherwise be difficult to obtain. At the same time, AI can empower organizational decision-making, improve resource allocation efficiency, and optimize the distribution of internal resources [50]. These factors can positively affect business performance and related outcomes. In addition, AI has a positive effect on corporate innovation. Deep learning-based AI can significantly improve the efficiency of knowledge production, shorten trial-and-error cycles in R&D, and enhance R&D efficiency [51]. However, as research has advanced, a growing number of studies have pointed out that AI does not always exert an empowering effect and that excessive deployment of AI technology can negatively affect organizations and innovation [48]. When firms blindly and excessively deploy AI, it crowds out investment in other areas, such as R&D and green innovation, thereby creating a resource crowding-out effect. At the same time, overreliance on AI algorithms can diminish the independent thinking of a firm's R&D staff, leading to path dependence and stifling exploratory innovation [52].

2.3. Research Gaps

Building on the above literature review, although some studies have begun to examine the effects of AI adoption and green innovation ambidexterity (GIA) separately, the integration of AI adoption and GIA into the same framework remains relatively underexplored. Most studies have examined the effect of AI on green innovation as a whole [7,53]. Cassanego et al. [54] noted that AI technology influences green innovation by improving efficiency and reducing resource waste. Although Zhao, Cao and Liu [38] have begun to examine the effect of AI on GIA and have confirmed that AI capabilities can significantly enhance both exploratory and exploitative green innovation, their study still adopts a linear framework that assumes monotonically increasing effects of AI capabilities.

Existing literature has increasingly examined AI and GIA, providing a theoretical foundation for this study. However, research on AI and green innovation often treats green innovation as a unitary concept and has only partially addressed the ambidexterity dimension. Although recent studies have begun to distinguish between exploratory and exploitative green innovation, the analytical approach still tends to focus on separately testing the effect of AI on each type. Yet achieving ambidexterity is important for firms. As organizational ambidexterity theory suggests, firms benefit from possessing both exploitative and exploratory capabilities to enhance their competitiveness. Therefore, research on the balance of GIA merits further investigation. However, how AI affects this equilibrium has received relatively limited attention in the existing literature.

Second, green innovation is a complex, long-term R&D activity. The effect of technologies such as AI on green innovation remains contested. Some studies suggest that deploying AI can promote green innovation, whereas others argue that AI may reduce firms' innovation. However, current research has not yet fully examined whether this inconsistency stems from nonlinear effects between AI and green innovation.

Third, the boundary conditions of human–technology synergy remain underexplored; in particular, how CEO characteristics moderate the relationship between AI and GIA has not been systematically examined. As AI becomes more deeply embedded in organizations, its effectiveness increasingly depends on alignment with organizational human factors. However, the boundary conditions governing AI’s effect on GIA remain unclear. Within the theoretical framework of human–technology synergy, whether CEO background and experience moderate the relationship between AI adoption and GIA remains an open question.

3. Theoretical Analysis and Hypothesis Development

3.1. Organizational Ambidexterity Theory

According to the organizational ambidexterity theory [9,55], firms must possess both exploratory and exploitative capabilities to sustain competitiveness [56]. However, when both are pursued simultaneously within a firm, they compete for resources. Therefore, managers need to coordinate these two types of activities [57] to maintain organizational ambidexterity. Drawing on this theory, green innovation ambidexterity (GIA) can be divided into exploratory and exploitative green innovation, both of which need to be pursued simultaneously within a firm [58]. These two types of innovation play complementary and irreplaceable roles. Consequently, corporate sustainability requires a balance between exploratory and exploitative green innovation. However, pursuing both types of green innovation simultaneously inevitably creates challenges in resource allocation [59]. As a result, firms often experience an imbalance between exploratory and exploitative green innovation. Therefore, achieving GIA is a cornerstone of firms’ long-term sustainable development.

3.2. Dynamic Capabilities Theory

According to dynamic capabilities theory, dynamic capabilities refer to a firm’s capacity to sense opportunities, seize opportunities, and integrate and allocate resources in response to environmental changes [60]. Pursuing both exploratory and exploitative green innovation simultaneously requires not only abundant resources but also flexible dynamic capabilities to respond to the diverse contexts that firms face [13]. In this vein, dynamic capabilities serve as pivotal enablers of GIA [17]. First, opportunity-sensing capability enables firms to identify opportunities conducive to their green development [61], thereby laying the groundwork for both exploratory and exploitative green innovation. Second, opportunity-seizing capability reflects the managerial process of translating identified opportunities into actionable decisions, which is critical to realizing GIA. Third, resource integration and allocation capability represent management’s ability to redeploy limited resources across competing initiatives; this capability is particularly critical for supporting the coordinated development of GIA. As a pivotal digital tool reshaping corporate green R&D processes, AI can significantly influence firms’ dynamic capabilities [62,63]. Existing research suggests that AI can enhance dynamic capabilities, thereby positively affecting corporate green innovation. However, AI also poses challenges to firms [48]. Moderate levels of AI integration into the green R&D process can enhance a firm’s capabilities in sensing, seizing, and reconfiguring resources, thereby facilitating the synergistic development of GIA. In contrast, unconstrained and excessive AI adoption may lead to path dependence, weaken dynamic capabilities, and disrupt the balance between exploratory and exploitative green innovation.

3.3. AI Adoption Intensity, Dynamic Capabilities, and Green Innovation Ambidexterity

3.3.1. The Effect of AI Adoption Intensity on Green Innovation Ambidexterity

As a next-generation digital technology capable of simulating and augmenting human intelligence [64], AI possesses strong capabilities in information acquisition and processing, predictive analytics [65], and intelligent decision-making. These capabilities enable AI adoption to substantially influence firms' ability to identify opportunities, process complex information, and allocate resources effectively.

At relatively moderate levels, AI adoption can improve the efficiency of information acquisition and processing [66] and strengthen firms' capacity to optimize resource allocation. GIA requires firms to allocate limited resources effectively between exploratory and exploitative green innovation. By leveraging its information acquisition and recognition capabilities, AI can help firms identify and obtain the information and resources required for both types of green innovation in a timely manner. Moreover, advanced AI algorithms can facilitate the dynamic allocation and reallocation of organizational resources [38], helping firms distribute resources more efficiently between exploratory and exploitative green innovation and thereby promote GIA. AI can also provide substantial decision support [67]. By automating routine and repetitive tasks, AI reduces managerial information-processing burdens and frees managerial attention, enabling decision-makers to devote greater attention to coordinating exploratory and exploitative green innovation simultaneously.

However, as AI adoption becomes excessive, its marginal benefits may diminish and adverse organizational consequences may emerge. Excessive AI adoption can divert managerial attention, crowd out organizational resources, and reinforce path dependence [68], thereby undermining GIA. When investment in AI exceeds a certain level, firms may need to devote increasing amounts of managerial attention, financial resources, and human capital to the maintenance, integration, and upgrading of AI systems. Because both exploratory and exploitative green innovation are inherently resource-intensive and require sustained organizational inputs [69], excessive AI investment may crowd out resources that would otherwise be allocated to maintaining an appropriate balance between the two. In addition, excessive reliance on AI may encourage firms to favor data-driven optimization of existing technologies and routines. Consequently, firms may place greater emphasis on exploitative green innovation while reducing their commitment to the exploration of novel and uncertain green technologies [48], ultimately disrupting the balance between exploration and exploitation.

These competing effects suggest that the benefits of AI adoption are likely to dominate at low to moderate levels of adoption, whereas the costs associated with resource crowding-out, managerial attention diversion, and path dependence may become increasingly salient at higher levels. Therefore, the effect of AI adoption intensity on GIA is expected to be nonlinear: GIA initially increases as AI adoption intensity rises, but declines once AI adoption exceeds an optimal level.

Based on the above arguments, we propose:

H1a. *AI adoption intensity has an inverted U-shaped relationship with GIA.*

3.3.2. The Mediating Role of Dynamic Capabilities

Drawing on organizational ambidexterity theory and dynamic capabilities theory, this study argues that AI adoption first strengthens and then erodes dynamic capabilities [70], thereby exerting an inverted U-shaped effect on GIA.

On the one hand, moderate AI adoption promotes GIA by strengthening firms' dynamic capabilities, and this mechanism operates through the core dimensions of dynamic

capabilities. Advancing GIA relies heavily on firms' ability to sense and seize external green opportunities [29], as well as their ability to integrate and allocate resources. First, AI adoption enhances firms' opportunity-sensing capabilities and mitigates information asymmetry [4,71]. For exploitative green innovation, AI can help firms accurately identify the optimization direction of existing green technologies, processes, and products. For exploratory green innovation, by leveraging deep learning algorithms, firms can comprehensively monitor trends in green and low-carbon technology evolution and make forward-looking predictions about future green innovation directions. This dual enhancement can significantly narrow the opportunity-identification gap between the two types of green innovation and promote GIA. Second, firms' ability to translate opportunities into concrete green R&D actions—that is, their opportunity-seizing capability—is also a key factor shaping GIA. AI-driven intelligent simulation models can provide end-to-end technical support for GIA. Simulation and parameter optimization techniques can reduce trial-and-error costs in green innovation, streamline the R&D process [72], and simultaneously improve the implementation efficiency of both types of green innovation activities. This fosters synergy between the two in terms of R&D pace and mitigates structural imbalances in GIA arising from inconsistent R&D processes. Third, balancing resource investment in GIA depends on firms' ability to dynamically allocate and integrate internal resources. AI adoption can enhance the automation and intelligence of resource allocation and integration processes [7]. Leveraging AI, firms can integrate diverse resource stocks—such as human capital, financial capital, and technology—into a unified intelligent analytical model, calculate the optimal resource allocation for GIA in real time, and dynamically schedule resources across different innovation activities. This allocation mode can secure essential resource inputs for exploitative green innovation and consolidate existing technological advantages. It can also provide flexible resource support for exploratory green innovation, expand technological frontiers, and promote coordinated resource investment in both types of green innovation, thereby enhancing GIA.

On the other hand, excessive AI adoption can hinder firms' innovation activities [73], erode dynamic capabilities, and inhibit GIA. First, unrestrained AI adoption can cause information overload and impose substantial cognitive burdens on managers. Managerial attention is a scarce resource, and the simultaneous influx of fragmented and voluminous information can divert and deplete managers' limited attention, weaken their ability to sense green innovation opportunities [74], and reduce their capacity to assess the coordinated development of GIA. In addition, exploratory green innovation requires deeper recognition of opportunities and is thus more vulnerable to erosion when attention is scattered. This further amplifies the asymmetry in opportunity recognition between the two types of innovation, thereby inhibiting GIA. Second, excessive AI deployment can induce path dependence, causing firms' green innovation decisions to rely heavily on model outputs. In such cases, firms lose their capacity for autonomous decision-making in coordinating ambidextrous green innovation projects, thereby fundamentally undermining their opportunity-seizing capability [13]. Specifically, AI can decompose existing technological parameters, reinforce the existing development trajectory of exploitative green innovation, and induce innovation inertia. Meanwhile, excessive algorithmic constraints can hinder breakthroughs in original green technologies, thereby suppressing firms' exploratory green innovation [48] and ultimately weakening GIA. Finally, excessive AI deployment can also impose operational burdens on firms [75], weakening their resource allocation capabilities. To support the deployment and operation of large-scale AI systems, firms need to continuously invest resources in computing power procurement, model iteration, and algorithm operation and maintenance. This can crowd out resources that could otherwise be dynamically allocated across exploratory and exploitative green innovation, thereby undermining

the resource-allocation mechanism underlying GIA and weakening the firm's resource allocation and integration capability. When resource allocation capability is insufficient, firms struggle to allocate limited resources across different projects, thereby inhibiting GIA.

Based on the above discussion, the following hypothesis can be proposed:

H1b. *Dynamic capabilities mediate the relationship between AI adoption intensity and GIA.*

3.4. The Moderating Effect of CEO IT Background

CEO IT background refers to whether a CEO has educational or professional experience in information technology or related fields. Previous studies have shown that CEOs with IT backgrounds possess extensive IT knowledge [76], which complements and helps correct the limitations of AI technology. Accordingly, we argue that CEO IT background can attenuate the effect of AI adoption intensity on GIA.

CEOs with IT backgrounds possess both technical expertise and managerial responsibilities [77]. Accordingly, they exercise greater control over AI technology. At a given level of AI adoption intensity, CEOs with and without IT backgrounds differ substantially in their opportunity-sensing, opportunity-seizing, and resource integration and allocation capabilities. On the one hand, within a moderate range of AI adoption intensity, AI adoption promotes GIA because AI tools enhance firms' opportunity-sensing, opportunity-seizing, and resource integration and allocation capabilities [78]. CEOs with IT backgrounds already possess a deeper understanding of information technologies such as AI; they tend to approach AI-driven decisions with caution [79] and do not rely solely on AI judgments when configuring GIA. Accordingly, the positive effect of AI adoption on GIA is attenuated. On the other hand, excessive AI adoption may erode firms' dynamic capabilities. CEOs with IT backgrounds can more accurately identify the cognitive burdens and resource dissipation associated with large-scale AI deployment and leverage their expertise to address the challenges firms face, thereby mitigating potential risks and adverse effects [75] and attenuating the effect of AI adoption intensity on GIA.

Taken together, the preceding arguments lead to the following hypothesis:

H2. *CEO's IT background attenuates the inverted U-shaped relationship between AI adoption intensity and GIA.*

3.5. The Moderating Effect of CEO Green Experience

According to dynamic capabilities theory, the effect of AI adoption intensity on GIA depends on the strength of a firm's dynamic capabilities. CEO green experience refers to whether a CEO has educational or professional experience related to environmental protection [75]. Such experience significantly enhances CEOs' green knowledge and cognition and strengthens their capacity for opportunity sensing, opportunity seizing, and resource integration and allocation in green initiatives. This reduces firms' reliance on AI adoption [18], thereby attenuating the effect of AI on GIA.

On the one hand, when AI adoption intensity falls within a moderate range, although AI can facilitate opportunity identification and capture in green innovation, the technology remains immature. The influence of CEO green experience on green innovation is more direct than that of AI technology. Therefore, CEOs with green experience tend to rely on their own cognition and experience to formulate green development strategies [80] and to sense and seize green innovation opportunities. They also possess substantial experience in integrating and allocating the resources required for GIA. This reduces firms' reliance on AI technology, thereby attenuating the positive effect of AI on GIA.

On the other hand, excessive AI adoption intensity can adversely affect GIA. In such cases, CEOs with green experience are more likely to recognize the AI-induced erosion of GIA. They can leverage their green knowledge and experience to sustain the strategic goal of balanced GIA development, thereby attenuating the adverse effect of excessive AI adoption intensity on GIA.

Based on the above discussion, we propose the following hypothesis:

H3. *CEO green experience attenuates the inverted U-shaped relationship between AI adoption intensity and GIA.*

3.6. The Secondary Moderating Effect of CEO Power

The above analysis suggests that CEO IT background and green experience can moderate the relationship between AI adoption intensity and GIA. However, a CEO's background generally shapes only their understanding of a project, and whether this understanding can be translated into action ultimately depends on CEO power [77,81]. CEO power refers to a CEO's influence over strategic decisions [82]. Given that the CEO is the primary decision-maker of corporate strategy, existing studies suggest that CEOs have sufficient power to influence a range of strategic activities, including corporate innovation [25,83], internationalization [84], and other business management activities [85]. Accordingly, we argue that CEO power shapes the moderating effects of CEO IT background and green experience.

The CEO occupies a central position within the top management team, and stakeholders expect the CEO to serve as the primary decision-maker for activities such as corporate innovation [25]. Accordingly, greater CEO power implies stronger influence over strategic decisions. In this context, CEO IT background and green experience are more likely to translate into strategic decisions and exert stronger moderating effects on the AI adoption intensity–GIA relationship. When CEO power is high, CEOs have greater influence over corporate decisions [25]. In such cases, the cautious stance of CEOs with IT backgrounds toward the extent of AI adoption is more likely to be reflected in firm decisions [77], thereby attenuating the effect of AI adoption intensity on GIA. At the same time, CEOs with green experience can more effectively articulate their green cognition and views and integrate green knowledge into green innovation activities, thereby strengthening GIA and attenuating the effect of AI adoption intensity. Conversely, when CEO power is low, even CEOs with an IT background or green experience have limited influence, making it difficult for their personal cognition to be incorporated into GIA-related decisions. As a result, the moderating effects of CEO IT background and green experience on the AI adoption intensity–GIA relationship are attenuated.

Based on the above discussion, we propose the following hypothesis:

H4. *CEO power strengthens the moderating effect of CEO IT background and CEO green experience on the AI adoption intensity–GIA relationship.*

Based on the above theoretical analysis and hypotheses, we construct a theoretical framework, as shown in Figure 1.

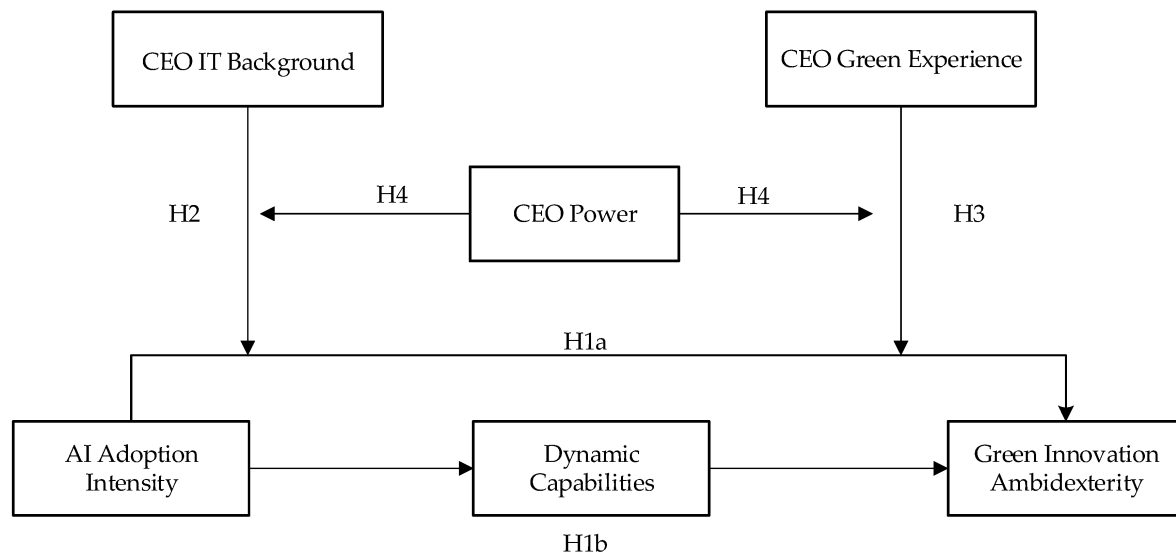


Figure 1. Theoretical Framework.

4. Methodology

4.1. Sample and Data

This study uses Chinese A-share listed firms over the period 2011–2025 as the initial sample. We select 2011 as the starting year because of its institutional relevance to the nexus between technology adoption and green innovation in China. Specifically, 2011 was the first full calendar year after the State Council’s 2010 decision to promote strategic emerging industries, including next-generation information technology as well as energy conservation and environmental protection. In addition, ministerial guidelines issued in 2011 explicitly emphasized the integration of information technology with environmental protection and resource-saving technologies. These developments provide an institutional context relevant to examining AI adoption and green innovation ambidexterity among Chinese A-share listed firms over 2011–2025. We obtain financial data from the CSMAR database, green patent data from the CNRDS database, and textual data from annual reports via the CNINFO website; web crawling and processing are conducted using Python 3.10.9. To ensure the objectivity and accuracy of the sample and results, we apply the following screening criteria: (1) exclude firms with ST, *ST, or PT status; (2) exclude financial firms; (3) exclude observations for which both exploratory and exploitative green innovation values are zero; and (4) exclude firms with missing data. After these procedures, the final sample comprises 2162 listed companies and 10,113 firm-year observations. To mitigate the effects of extreme outliers, we winsorize all continuous variables at the 1st and 99th percentiles.

4.2. Measures

4.2.1. Dependent Variable—Green Innovation Ambidexterity (GIA)

Green innovation ambidexterity is generally divided into exploratory and exploitative green innovation [57,86,87]. Following prior studies, we adopt a two-step approach to construct the GIA variable. In the first step, we measure exploratory and exploitative green innovation. Prior studies often measure green innovation by the number of green patent applications. Therefore, following Liu and Yang [86] and Lu [11], we measure exploratory green innovation by the number of green invention patent applications and exploitative green innovation by the number of green utility model patent applications. In the second step, drawing on You et al. [88] and Zhong and Zhang [13], we calculate the absolute difference between exploratory and exploitative green innovation. This indicator ranges

from 0 to 843. Finally, following Zhong and Zhang [13], we measure GIA as 843 minus the absolute difference. A higher value indicates greater green innovation ambidexterity. Because ambidexterity is not meaningful when both exploratory and exploitative green innovation are zero, we exclude observations in which both types are zero.

4.2.2. Independent Variable—AI Adoption Intensity (AI)

The prevailing method for measuring AI adoption intensity is to count the frequency of AI-related keywords in annual reports. Following Guo, Pei and Liu [4], we measure AI adoption intensity as the natural logarithm of one plus the frequency of AI-related keywords in listed firms' annual reports. Drawing on Zhao et al. [89] and Cheng et al. [90], we adopt the following keywords to measure AI adoption: artificial intelligence, business intelligence, image understanding, investment decision aid systems, intelligent data analysis, intelligent robotics, machine learning, deep learning, semantic search, biometric recognition technology, face recognition, speech recognition, identity verification, autonomous driving, natural language processing, and intelligent.

4.2.3. Mediating Variable—Dynamic Capabilities (DC)

According to Teece [60], dynamic capabilities constitute a multidimensional construct comprising three interrelated sub-dimensions: opportunity sensing, opportunity seizing, and resource integration and reconfiguration. To capture the overall level of dynamic capabilities, we integrate these three dimensions into a composite measure. Following prior studies, we adopt a two-step approach to construct the DC. First, following Li et al. [91], we measure opportunity-sensing capability using the coefficients of variation in advertising expenditure and corporate R&D investment. Opportunity-seizing capability is commonly proxied by R&D investment intensity [13], we measure it as the ratio of the annual increase in R&D expenditure to operating revenue. Drawing on Wang and Huang [92], we measure resource integration and reconfiguration capability using the total asset turnover ratio, calculated as operating revenue divided by total assets. Second, because these three dimensions are interrelated and jointly constitute a firm's dynamic capabilities, and drawing on Wang and Huang [92], we employ the entropy weight method to integrate the three capabilities into a composite index to measure DC. The entropy weight method is an objective weighting approach in which weights are determined by the dispersion inherent in each indicator's data. This method helps mitigate biases arising from subjective weighting, making it particularly suitable for constructing multidimensional composite constructs such as dynamic capabilities.

4.2.4. Moderating Variable—CEO IT Background (IT)

CEO IT background refers to whether a CEO has educational, professional, or work experience related to information technology [79]. Drawing on Haislip and Richardson [22] and Sun, Zhang, Zhu, Mao and Liang [77], we measure CEO IT background by identifying whether a CEO's resume contains IT-related keywords, including CIO, Chief Information Officer, CTO, Chief Technology Officer, computer technology, computer science, information systems, IT vice president, IT consultant, software engineer, and system engineer. CEOs whose resumes contain any such keywords are coded as 1 for CEO IT background and 0 otherwise.

4.2.5. Moderating Variable—CEO Green Experience (Green)

CEO green experience refers to whether a CEO has educational or professional experience related to green environmental protection [93]. Drawing on Deng et al. [94], we measure CEO green experience by whether a CEO's resume contains keywords related to green environmental protection. The relevant keywords are as follows: green,

environmental protection, environment, recycling, reuse, pollution, ecology, emissions reduction, energy conservation, environmental impact assessment, clean energy, clean production, solid waste, air emissions, carbon trading, carbon emissions, carbon neutrality, carbon management, wind power, photovoltaics, hydrogen energy, and solar energy. CEOs whose resumes contain any such keywords are coded as 1 for CEO green experience and 0 otherwise.

4.2.6. Moderating Variable—CEO Power (Power)

CEO power refers to a CEO's ability to exercise their will and influence strategic decisions, and it comprises four dimensions: structural power, ownership power, expert power, and prestige power [82]. Drawing on Sun, Zhang, Zhu, Mao and Liang [77], we measure CEO power by summing the four dummy variables corresponding to these dimensions (when a firm has multiple CEOs in a given year, we use the average value). Specifically, structural power is measured by whether the CEO serves as chairman. Ownership power is measured by whether the CEO holds equity. Expert power is measured by the breadth of professional backgrounds, coded as 1 if the CEO has two or more professional backgrounds and 0 otherwise. Prestige power is measured by whether the CEO also serves as a director of other listed firms.

4.2.7. Control Variables

To ensure the robustness and reliability of the regression models and results, we include other factors that may affect GIA as control variables. These include firm size (Size), leverage (Lev), largest shareholder ownership (Top1), ownership nature (State), firm growth (Growth), R&D investment (lnRD), firm age (Age), board shareholding (DH), and board size (DN). We also include year and firm fixed effects to control for year- and firm-specific influences on GIA. Table 1 presents the definitions and measurements of all variables.

Table 1. Variable Definition and Measurement.

Variable Properties	Variable Name	Code	Variable Measurement	Reference
Dependent variable	Green innovation ambidexterity	GIA	843 minus the absolute difference between exploratory and exploitative green innovation	Zhong and Zhang [13]
Independent variable	AI adoption intensity	AI	Natural logarithm of one plus the frequency of AI-related keywords in listed firms' annual reports	Zhao, Li, Li and Wang [89] Cheng, Lin and Hong [90]
Mediating variable	Dynamic capability	DC	Constructing a composite index using the entropy weight method	Wang and Huang [92]
Moderating variable	CEO IT background	IT	Whether the CEO's resume contains IT-related keywords	Sun, Zhang, Zhu, Mao and Liang [77]
	CEO green experience	Green	Whether the CEO's resume contains keywords related to green or environmental protection	Deng, Tang and Luo [94],
	CEO power	Power	Sum of the dummy variables for the four dimensions	Sun, Zhang, Zhu, Mao and Liang [77]

Table 1. Cont.

Variable Properties	Variable Name	Code	Variable Measurement	Reference
Control variables	Firm size	Size	Natural logarithm of total assets	Wang et al. [95]
	Leverage ratio	Lev	Total liabilities/total assets	Wang, Zhang, Ren and Shi [95]
	Shareholding ratio of the largest shareholder	Top1	Shareholding ratio of the largest shareholder	Wang, Zhang, Ren and Shi [95]
	Ownership nature	State	Coded as 1 if the firm is state-owned and 0 otherwise	Usman et al. [96]
	Firm growth	Growth	Operating revenue growth rate	Wang et al. [97]
	R&D investment	lnRD	Natural logarithm of one plus R&D investment	Wang, Wang, Wu, Zhai and Li [97]
	Firm age	Age	Natural logarithm of firm age, measured as current year minus listing year plus one	Wang, Zhang, Ren and Shi [95]
	Board shareholding	DH	Natural logarithm of one plus the number of shares held by the board	Usman, Javed and Yin [96]
	Board size	DN	Natural logarithm of one plus the number of directors	Tawiah et al. [98]

4.3. Empirical Model

To determine the appropriate panel data model, we performed a Hausman test. Because the traditional Hausman test may suffer from a non-positive-definite covariance matrix, we employed a modified Hausman test (sigmamore). The test results indicate that the chi-square statistic is 94.84 and the p -value (Prob > chi2) is 0.000, thereby strongly rejecting the null hypothesis at the 1% significance level. Accordingly, we selected the fixed-effects model for the baseline regression analysis. To mitigate the influence of time-invariant firm-specific attributes and temporal shocks on our estimates, we include firm and year fixed effects. The empirical model is specified as follows:

$$GIA_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 AI_{it}^2 + \beta_3 Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

$$DC_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 AI_{it}^2 + \beta_3 Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

$$GIA_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 AI_{it}^2 + \beta_3 DC_{it} + \beta_4 Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (3)$$

$$GIA_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 AI_{it}^2 + \beta_3 IT_{it}/Green_{it} + \beta_4 IT_{it}/Green_{it} \times AI_{it} + \beta_5 IT_{it}/Green_{it} \times AI_{it}^2 + \beta_6 Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (4)$$

$$GIA_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 AI_{it}^2 + \beta_3 IT_{it}/Green_{it} + \beta_4 IT_{it}/Green_{it} \times AI_{it} + \beta_5 IT_{it}/Green_{it} \times AI_{it}^2 + \beta_6 Power_{it} + \beta_7 IT_{it}/Green_{it} \times AI_{it} \times Power_{it} + \beta_8 IT_{it}/Green_{it} \times AI_{it}^2 \times Power_{it} + \beta_9 Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (5)$$

5. Empirical Results

5.1. Descriptive Results

Table 2 presents the descriptive statistics. The mean of the GIA is 835.309, with a standard deviation of 28.621, indicating considerable variation in green innovation ambidexterity across sample firms. The mean of AI adoption intensity is 1.562, with a standard deviation of 1.190 and a range from 0.000 to 4.477, suggesting that the average level of AI adoption intensity is relatively low to moderate. Descriptive statistics for the other variables are largely consistent with prior research.

Table 2. Descriptive Statistical Results.

Variable	Observations	Mean	SD	Min	Max
GIA	10,113	835.309	28.621	0.000	843.000
AI	10,113	1.562	1.190	0.000	4.477
DC	10,113	0.361	0.070	0.269	0.564
IT	10,113	0.013	0.115	0.000	1.000
Green	10,113	0.082	0.274	0.000	1.000
Power	10,113	1.654	0.852	0.000	4.000
Size	10,113	22.606	1.279	20.312	26.438
Lev	10,113	0.449	0.192	0.080	0.908
Top1	10,113	32.479	14.276	8.260	71.240
State	10,113	0.346	0.476	0.000	1.000
Growth	10,113	0.288	0.646	−0.714	3.860
lnRD	10,113	18.575	1.382	15.056	22.473
Age	10,113	2.260	0.764	0.693	3.434
DH	10,113	12.963	7.038	0.000	20.445
DN	10,113	2.234	0.173	1.792	2.708

5.2. Benchmark Regression Results

All continuous variables involved in interaction terms are mean-centered to mitigate multicollinearity. Table 3 reports the baseline regression results from the fixed-effects model. Column (1) reports the effect of AI adoption intensity on GIA. The results indicate that AI² has a significantly negative coefficient ($\beta = -1.310$, $p < 0.01$), supporting Hypothesis 1a. Columns (2) and (3) examine the mediating role of dynamic capabilities (DC). Column (2) shows that the coefficient of AI² is significantly negative ($\beta = -0.001$, $p < 0.05$), indicating that AI has a significant inverted U-shaped effect on DC; Column (3) shows that the coefficient of DC is significantly positive ($\beta = 15.339$, $p < 0.01$), indicating that DC positively affects GIA. These results confirm that AI adoption intensity influences GIA through DC, thereby supporting Hypothesis 1b.

Table 3. Benchmark Regression Results.

	(1) GIA	(2) DC	(3) GIA	(4) GIA	(5) GIA	(6) GIA	(7) GIA
AI	−0.776 ** (0.365)	−0.002 * (0.001)	−0.745 ** (0.365)	−0.690 * (0.366)	−0.676 * (0.366)	−0.678 * (0.372)	−0.659 * (0.372)
AI ²	−1.310 *** (0.193)	−0.001 ** (0.001)	−1.290 *** (0.192)	−1.362 *** (0.195)	−1.370 *** (0.195)	−1.442 *** (0.199)	−1.439 *** (0.199)
DC			15.339 *** (3.953)				
IT				−4.317 (3.541)	−5.055 (3.610)		
IT × AI				−19.318 *** (3.506)	−38.228 *** (7.868)		
IT × AI ²				7.769 *** (1.450)	15.682 *** (3.886)		
Power					−0.967 ** (0.409)		−1.011 ** (0.416)
IT × AI × Power					11.539 *** (4.302)		
IT × AI ² × Power					−4.822 ** (2.179)		
Green						−3.055 ** (1.387)	−2.889 ** (1.390)
Green × AI						−0.356 (0.891)	0.242 (1.823)
Green × AI ²						1.729 ** (0.692)	0.884 (1.317)
Green × AI × Power							−0.398 (0.941)
Green × AI ² × Power							0.470 (0.622)

Table 3. Cont.

	(1) GIA	(2) DC	(3) GIA	(4) GIA	(5) GIA	(6) GIA	(7) GIA
Size	−4.582 *** (0.789)	−0.005 ** (0.002)	−4.500 *** (0.789)	−4.731 *** (0.788)	−4.692 *** (0.788)	−4.602 *** (0.789)	−4.546 *** (0.789)
Lev	8.887 *** (2.579)	0.014 * (0.007)	8.673 *** (2.577)	9.202 *** (2.574)	8.966 *** (2.574)	9.126 *** (2.579)	9.231 *** (2.581)
Top1	0.112 ** (0.044)	0.001 *** (0.000)	0.104 ** (0.044)	0.105 ** (0.044)	0.101 ** (0.044)	0.110 ** (0.044)	0.109 ** (0.044)
State	−2.409 (1.544)	0.002 (0.004)	−2.442 (1.542)	−2.374 (1.543)	−2.538 (1.545)	−2.292 (1.545)	−2.489 (1.547)
Growth	0.543 (0.443)	0.007 *** (0.001)	0.442 (0.444)	0.547 (0.443)	0.513 (0.442)	0.557 (0.443)	0.558 (0.443)
lnRD	−0.856 (0.522)	0.007 *** (0.001)	−0.963 * (0.523)	−0.791 (0.521)	−0.742 (0.521)	−0.880 * (0.522)	−0.867 * (0.522)
Age	6.846 *** (1.171)	0.018 *** (0.003)	6.576 *** (1.172)	6.936 *** (1.169)	6.702 *** (1.171)	6.869 *** (1.171)	6.713 *** (1.174)
DH	−0.199 *** (0.063)	−0.000*** (0.000)	−0.191 *** (0.063)	−0.200 *** (0.063)	−0.163 ** (0.065)	−0.198 *** (0.063)	−0.156 ** (0.065)
DN	0.164 (2.411)	−0.005 (0.007)	0.244 (2.409)	0.664 (2.408)	0.451 (2.412)	0.152 (2.410)	−0.246 (2.415)
Constant	944.600 *** (14.740)	0.335 *** (0.042)	939.461 *** (14.787)	945.678 *** (14.713)	946.255 *** (14.714)	945.710 *** (14.742)	946.519 *** (14.751)
Year	YES	YES	YES	YES	YES	YES	YES
Firm	YES	YES	YES	YES	YES	YES	YES
Observations	10,113	10,113	10,113	10,113	10,113	10,113	10,113
R-squared	0.060	0.032	0.062	0.064	0.066	0.061	0.062

Note: AI and AI² are mean-centered. Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Columns (4) and (6) report the moderating effects of CEO IT background and CEO green experience, respectively. The coefficient $\times t$ of IT*AI² is significantly positive ($\beta = 7.769$, $p < 0.01$). The coefficient of Green*AI² is significantly positive ($\beta = 1.729$, $p < 0.05$). These results indicate that both CEO IT background and CEO green experience attenuate the effect of AI adoption intensity on GIA, supporting Hypotheses 2 and 3. Columns (5) and (7) display the second-order moderating effects of CEO power on each of the two moderators, respectively. The coefficient of IT*AI²*Power is significantly negative ($\beta = -4.822$, $p < 0.05$), indicating that CEO power attenuates the moderating effect of CEO IT background. However, the coefficient of Green*AI²*Power is not significant ($\beta = 0.470$, $p > 0.1$). Therefore, Hypothesis 4 is not supported, as discussed in the “Findings and Discussion” section.

To verify the inverted U-shaped relationship, we performed a U-test. Table 4 reports the U-test results, which indicate that the inverted U-shaped relationship between AI adoption intensity and GIA is statistically significant ($p < 0.000$). The slope on the left side of the curve is 3.317 ($t = 4.697$), whereas the slope on the right side is -8.417 ($t = -7.146$). Both slopes are statistically significant, further confirming the inverted U-shaped relationship. The estimated turning point is -0.296 (the range of mean-centered AI is -1.562 to 2.916), with a 95% confidence interval of $[-0.624, -0.023]$.

Table 4. U-test Results.

Overall test of the inverted U-shaped relationship (Fieller)	$t\text{-value} = 4.70, p > t = 0.000$
Variable range	95% Fieller interval for extreme point: $[-0.624; -0.023]$
Turning point	-0.296
Left-side slope of the curve and t-statistic	Slope = 3.317, $t = 4.697$
Left-side slope of the curve and t-statistic	Slope = -8.417 , $t = -7.146$

Note: The left column presents test items, and the right column reports corresponding results.

5.3. Robustness Test

5.3.1. Exclude the Information Industry

The information industry is technology-intensive. Firms in this industry tend to adopt AI earlier and exhibit higher AI adoption intensity, which may affect the results. Therefore, in the robustness test, we exclude firms in the “software and information technology services” industry. The regression results are reported in Table 5. The coefficient of AI² on GIA remains significantly negative. The coefficient of AI² on DC remains significantly negative, and the coefficient of DC on GIA is significantly positive. The coefficients of IT*AI² and Green*AI² remain positive. The coefficient of IT*AI²*Power is negative.

Table 5. Robustness Results Test—Exclude the Information Industry.

	(1) GIA	(2) DC	(3) GIA	(4) GIA	(5) GIA	(6) GIA	(7) GIA
AI	−0.617 *	−0.002 **	−0.601 *	−0.597 *	−0.595 *	−0.503	−0.490
AI ²	−0.867 ***	−0.002 ***	−0.853 ***	−0.893 ***	−0.895 ***	−1.007 ***	−1.005 ***
DC			7.534 **				
IT			(3.403)	−22.435 ***	−23.339 ***		
IT × AI				(4.251)	(4.393)		
IT × AI ²				−2.056	−9.123		
Power				(4.527)	(10.881)		
IT × AI × Power				1.213	9.707		
IT × AI ² × Power				(2.432)	(7.004)		
Green					−0.739 **		−0.804 **
Green × AI					(0.352)		(0.359)
Green × AI ²					5.991		
Green × AI × Power					(6.965)		
Green × AI ² × Power					−5.954		
Constant	891.222 ***	0.333 ***	888.712 ***	890.680 ***	891.189 ***	892.186 ***	892.531 ***
Controls	(12.672)	(0.044)	(12.719)	(12.634)	(12.638)	(12.673)	(12.685)
Year	YES	YES	YES	YES	YES	YES	YES
Firm	YES	YES	YES	YES	YES	YES	YES
Observations	9325	9325	9325	9325	9325	9325	9325
R-squared	0.054	0.030	0.054	0.060	0.061	0.055	0.056

Note: AI and AI² are mean-centered. Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.3.2. Excluding the Sample in 2020

Because a major public health event in 2020 affected listed firms, we exclude the 2020 sample in a robustness test. The re-estimated results are reported in Table 6. They are largely consistent with the baseline regression.

5.3.3. Cluster-Robust Standard Errors

The baseline regression did not employ clustered standard errors. To mitigate potential bias in statistical inference due to heteroscedasticity, we re-estimated the model with firm-clustered robust standard errors in the robustness analysis. The regression results are reported in Table 7. They are largely consistent with the baseline regression.

Table 6. Robustness Results Test—Excluding the Sample in 2020.

	(1) GIA	(2) DC	(3) GIA	(4) GIA	(5) GIA	(6) GIA	(7) GIA
AI	−0.634 (0.394)	−0.002 * (0.001)	−0.604 (0.393)	−0.532 (0.394)	−0.512 (0.394)	−0.511 (0.402)	−0.485 (0.402)
AI ²	−1.437 *** (0.206)	−0.001 ** (0.001)	−1.417 *** (0.206)	−1.492 *** (0.209)	−1.504 *** (0.209)	−1.591 *** (0.212)	−1.590 *** (0.212)
DC			15.844 *** (4.272)				
IT				−4.809 (3.738)	−5.487 (3.817)		
IT × AI				−20.667 *** (3.706)	−39.582 *** (8.375)		
IT × AI ²				8.183 *** (1.524)	15.825 *** (4.055)		
Power					−0.914 ** (0.440)		−0.965 ** (0.448)
IT × AI × Power					11.732 ** (4.669)		
IT × AI ² × Power					−4.760 ** (2.297)		
Green						−3.464 ** (1.510)	−3.328 ** (1.513)
Green × AI						−0.417 (0.954)	0.584 (1.911)
Green × AI ²						2.028 *** (0.742)	1.186 (1.385)
Green × AI × Power							−0.641 (0.990)
Green × AI ² × Power							0.471 (0.651)
Constant	950.151 *** (15.632)	0.336 *** (0.043)	944.830 *** (15.684)	951.636 *** (15.600)	952.194 *** (15.602)	951.537 *** (15.634)	952.209 *** (15.644)
Controls	YES	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES
Firm	YES	YES	YES	YES	YES	YES	YES
Observations	9243	9243	9243	9243	9243	9243	9243
R-squared	0.063	0.034	0.065	0.068	0.069	0.064	0.065

Note: AI and AI² are mean-centered. Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7. Robustness Results Test—Cluster-Robust Standard Errors.

	(1) GIA	(2) DC	(3) GIA	(4) GIA	(5) GIA	(6) GIA	(7) GIA
AI	−0.776 (0.474)	−0.002 (0.001)	−0.745 (0.468)	−0.690 (0.463)	−0.676 (0.460)	−0.678 (0.480)	−0.659 (0.476)
AI ²	−1.310 * (0.705)	−0.001 * (0.001)	−1.290 * (0.694)	−1.362 * (0.722)	−1.370 * (0.722)	−1.442 ** (0.735)	−1.439 * (0.734)
DC			15.339 * (8.261)				
IT				−4.317 (15.188)	−5.055 (14.548)		
IT × AI				−19.318 (13.674)	−38.228 (29.238)		
IT × AI ²				7.769 * (4.133)	15.682 (10.651)		
Power					−0.967 ** (0.473)		−1.011 ** (0.488)
IT × AI × Power					11.539 (10.192)		
IT × AI ² × Power					−4.822 (4.172)		
Green						−3.055 ** (1.354)	−2.889 ** (1.312)
Green × AI						−0.356 (0.894)	0.242 (1.714)

Table 7. Cont.

	(1) GIA	(2) DC	(3) GIA	(4) GIA	(5) GIA	(6) GIA	(7) GIA
Green $\times$ AI ²						1.729 ** (0.734)	0.884 (0.755)
Green $\times$ AI $\times$ Power							−0.398 (0.996)
Green $\times$ AI ² $\times$ Power							0.470 (0.456)
Constant	936.263 *** (46.685)	0.304 *** (0.071)	931.596 *** (44.604)	937.371 *** (46.549)	938.016 *** (46.845)	937.276 *** (46.837)	938.206 *** (47.084)
Controls	YES	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES
Firm	YES	YES	YES	YES	YES	YES	YES
Observations	9694	9694	9694	9694	9694	9694	9694
R-squared	0.678	0.532	0.679	0.680	0.680	0.679	0.679

Note: AI and AI² are mean-centered. Robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.3.4. Replacing the Independent Variable

Given that measuring AI adoption through word frequency in annual reports may raise concerns about strategic disclosure, we also measured AI adoption intensity as the natural logarithm of one plus total AI investment and re-estimated the regression. The regression results are reported in Table 8. These results are consistent with the baseline results.

Table 8. Reinglace the Independent Variable.

	(1) GIA	(2) DC	(3) GIA	(4) GIA	(5) GIA	(6) GIA	(7) GIA
AI	−2.507 *** (0.397)	−0.002 * (0.001)	−2.475 *** (0.396)	−2.509 *** (0.396)	−2.422 *** (0.394)	−2.517 *** (0.400)	−2.557 *** (0.400)
AI ²	−1.095 *** (0.074)	−0.001 *** (0.000)	−1.086 *** (0.074)	−1.116 *** (0.073)	−1.066 *** (0.073)	−1.103 *** (0.074)	−1.108 *** (0.074)
DC			15.492 *** (4.221)				
IT				−18.947 *** (3.491)	−13.912 *** (3.512)		
IT $\times$ AI				−4.992 *** (1.873)	−1.381 (4.276)		
IT $\times$ AI ²				3.146 *** (0.430)	8.277 *** (0.956)		
Power					−1.065 ** (0.431)		−1.287 *** (0.441)
IT $\times$ AI $\times$ Power					0.182 (2.340)		
IT $\times$ AI ² $\times$ Power					−4.325 *** (0.627)		
Green						−1.215 (1.426)	−0.979 (1.427)
Green $\times$ AI						0.361 (0.640)	−0.037 (1.175)
Green $\times$ AI ²						0.223 (0.251)	−0.467 (0.434)
Green $\times$ AI $\times$ Power							0.500 (0.676)
Green $\times$ AI ² $\times$ Power							0.479 * (0.247)
Constant	917.065 *** (16.959)	0.279 *** (0.047)	912.735 *** (16.985)	917.702 *** (16.888)	920.829 *** (16.787)	917.939 *** (16.982)	919.643 *** (16.982)
Controls	YES	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES
Firm	YES	YES	YES	YES	YES	YES	YES
Observations	9349	9349	9349	9349	9349	9349	9349
R-squared	0.085	0.035	0.087	0.094	0.106	0.085	0.086

Note: AI and AI² are mean-centered. Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.3.5. Employing Alternative Econometric Specifications

To further assess the robustness of the results, we employ Poisson pseudo-maximum likelihood (PPML) estimation. This estimator can accommodate non-negative dependent variables. The regression results are reported in Table 9, and the key findings are consistent with the baseline results.

Table 9. Robustness Test Results—Employing Alternative Econometric Specifications.

	(1) GIA	(2) DC	(3) GIA	(4) GIA	(5) GIA	(6) GIA	(7) GIA
AI	−0.001 ** (0.000)	−0.006 ** (0.003)	−0.001 ** (0.000)	−0.001 ** (0.000)	−0.001 * (0.000)	−0.001 * (0.000)	−0.001 * (0.000)
AI ²	−0.002 *** (0.000)	−0.004 ** (0.002)	−0.002 *** (0.000)	−0.002 *** (0.000)	−0.002 *** (0.000)	−0.002 *** (0.000)	−0.002 *** (0.000)
DC			0.019 *** (0.006)				
IT				−0.005 (0.009)	−0.006 (0.009)		
IT × AI				−0.024 ** (0.010)	−0.048 * (0.026)		
IT × AI ²				0.010 *** (0.004)	0.020 * (0.011)		
Power					−0.001 *** (0.000)		−0.001 *** (0.000)
IT × AI × Power					0.015 (0.010)		
IT × AI ² × Power					−0.006 (0.004)		
Green						−0.004 *** (0.001)	−0.004 *** (0.001)
Green × AI						−0.000 (0.001)	0.000 (0.002)
Green × AI ²						0.002 *** (0.001)	0.001 (0.001)
Green × AI × Power							−0.000 (0.001)
Green × AI ² × Power							0.001 (0.000)
Constant	6.850 *** (0.022)	−1.173 *** (0.135)	6.844 *** (0.021)	6.851 *** (0.022)	6.852 *** (0.022)	6.851 *** (0.022)	6.853 *** (0.022)
Controls	YES	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES
Firm	YES	YES	YES	YES	YES	YES	YES
Observations	9694	9694	9694	9694	9694	9694	9694
Pseudo R ²	0.0801	0.00547	0.0802	0.0803	0.0803	0.0801	0.0802

Note: AI and AI² are mean-centered. Robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.3.6. Control Year and Industry Interaction

We further control for industry–year interaction effects. The results are reported in Table 10. They are consistent with the baseline results.

5.4. Endogeneity Test

5.4.1. Instrumental Variable Method

We use the instrumental variable method to address endogeneity concerns. Following related studies, we use the industry-year average of AI adoption intensity as the instrumental variable. Table 11 reports the instrumental variable regression results. As shown in columns (1) and (2), the coefficients of the instrumental variables (IV and IV²) are significantly positive, indicating that they are positively correlated with firm-level AI adoption intensity (AI and AI²). Column (3) shows that the coefficient of AI² on GIA remains significantly negative. In addition, the p -value of the LM test is less than 0.01, rejecting the null hypothesis of underidentification. The Cragg-Donald Wald F statistic is 57.941, which

is well above the Stock-Yogo critical value of 7.03 at the 10% level, suggesting that weak instruments are not a concern.

Table 10. Robustness Test Results—Control Year and Industry Interaction.

	(1) GIA	(2) DC	(3) GIA	(4) GIA	(5) GIA	(6) GIA	(7) GIA
AI	−0.405 (0.372)	−0.002 (0.001)	−0.383 (0.372)	−0.376 (0.372)	−0.349 (0.372)	−0.319 (0.378)	−0.302 (0.378)
AI ²	−0.788 *** (0.205)	−0.001 (0.001)	−0.776 *** (0.205)	−0.886 *** (0.206)	−0.880 *** (0.206)	−0.886 *** (0.211)	−0.879 *** (0.211)
DC			13.706 *** (3.996)				
IT				−8.536 ** (3.578)	−8.591 ** (3.637)		
IT × AI				−16.298 *** (3.585)	−38.497 *** (8.051)		
IT × AI ²				7.615 *** (1.474)	14.523 *** (3.971)		
Power					−1.034 ** (0.412)		−1.047 ** (0.418)
IT × AI × Power					13.149 *** (4.373)		
IT × AI ² × Power					−4.205 * (2.213)		
Green						−2.358 * (1.408)	−2.202 (1.412)
Green × AI						−0.510 (0.912)	−0.566 (1.857)
Green × AI ²						1.211 * (0.713)	0.546 (1.340)
Green × AI × Power							0.003 (0.948)
Green × AI ² × Power							0.362 (0.626)
Constant	940.381 *** (26.608)	0.290 *** (0.076)	936.403 *** (26.615)	941.126 *** (26.557)	940.720 *** (26.538)	941.050 *** (26.610)	941.705 *** (26.611)
Controls	YES	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES
Firm	YES	YES	YES	YES	YES	YES	YES
Observations	10,113	10,113	10,113	10,113	10,113	10,113	10,113
R-squared	0.093	0.063	0.094	0.097	0.099	0.093	0.094

Note: AI and AI² are mean-centered. Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 11. Endogeneity Test Results—Instrumental Variable Method.

	(1) First Stage (AI)	(2) First Stage (AI ²)	(3) Second Stage (GIA)
IV	0.458 *** (0.042)	−0.063 (0.076)	
IV ²	0.041 *** (0.015)	0.771 *** (0.027)	
AI			4.002 (3.098)
AI ²			−6.302 *** (0.743)
Constant	−4.454 *** (0.450)	0.109 (0.817)	
Controls	YES	YES	YES
Year	YES	YES	YES
Firm	YES	YES	YES
Observations	10,113	10,113	9694
F	244.712	52.579	19.948
LM			114.572, $p = 0.0000$
Cragg-Donald Wald F			57.941
Stock-Yogo 10% threshold for weak instrumental variables test			7.03

Note: IV, IV², AI and AI² are mean-centered. Standard errors in parentheses, *** $p < 0.01$.

5.4.2. Heckman Two-Stage Method

To control for self-selection bias, we employ the Heckman two-stage procedure. We use the industry-year median of AI adoption intensity as the cutoff to construct a dummy variable. If a firm's AI adoption intensity is above the median, the relative AI level (*Dum*) is coded as 1; otherwise, it is 0. In addition, we use the industry-year mean of AI adoption intensity of other firms in the same industry (excluding the focal firm) as the exclusion restriction variable (*Other*). We estimate the first-stage regression and compute the inverse Mills ratio (*IMR*). In the second stage, we include the *IMR* in the model and re-estimate the regression. The results are reported in columns (1) and (2) of Table 12, and they are consistent with the main findings.

Table 12. Endogeneity Test Results—Heckman Two-stage Method and PSM.

	(1) Dum	(2) GIA	(3) GIA	(4) GIA
<i>IMR</i>		−18.920 *** (7.035)		
<i>Other</i>	−0.246 *** (0.033)			
<i>AI</i>		−0.708 * (0.367)	−0.225 (0.357)	−0.776 ** (0.365)
<i>AI</i> ²		−1.238 *** (0.194)	−0.791 *** (0.196)	−1.310 *** (0.193)
Constant	−0.763 ** (0.311)	971.981 *** (17.882)	945.267 *** (14.961)	944.600 *** (14.740)
Controls	YES	YES	YES	Controls
Year	YES	YES	YES	Year
Firm	YES	YES	YES	Firm
Observations	10,094	10,094	7968	10,113
R-squared	-	0.061	0.058	0.060
Pseudo R-squared	0.0457	-	-	-

Note: *AI* and *AI*² are mean-centered. Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.4.3. Propensity Score Matching (PSM)

To further address endogeneity concerns, we also employ propensity score matching (PSM) as an additional test. We define firms with AI adoption intensity above the industry-year average as the treatment group and the remaining firms as the control group. We use 1:1 nearest-neighbor matching. The results are reported in columns (3) and (4) of Table 12. Column (3) reports the matched-sample results, and column (4) reports the full-sample results. These results are consistent with the baseline regression.

6. Heterogeneity Analyses

6.1. Industry Heterogeneity

Whether a firm operates in a heavy-polluting industry directly affects the intensity of environmental regulation it faces. Heavy-polluting firms face greater environmental pressure and are subject to more stringent environmental policy requirements. In response to environmental policies, heavy-polluting firms may either strengthen low-cost exploitative green innovation or enhance the balance of ambidextrous green innovation to achieve genuine green development. Therefore, we divide the sample according to whether firms belong to heavy-polluting industries. Following Zheng and Zhang [99] and China's List of Environmental Protection Verification Industry Classification and Management for Listed Companies, we classify 19 industry codes as heavy-polluting industries and the remaining codes as non-heavy-polluting industries (heavy-polluting industry codes: B06, B07, B08, B09, C15, C17, C18, C19, C22, C25, C26, C27, C28, C29, C30, C31, C32, D44, D45). The results are reported in columns (1) and (2) of Table 13. The coefficient of *AI*² is significant in non-heavy-polluting industries but not in heavy-polluting ones. Although this finding

may appear counterintuitive, it reflects the distinctive characteristics of heavy-polluting industries. Heavy-polluting industries face stringent environmental regulations, and their green innovation activities are often mandatory. Such external institutional constraints reduce firms' latitude to independently balance ambidextrous innovation, resulting in a weaker effect of AI adoption intensity on GIA. In contrast, non-heavy-polluting industries face relatively less environmental pressure and enjoy greater strategic freedom. This allows AI adoption intensity to exert a more pronounced influence on GIA.

Table 13. Heterogeneity test.

	(1) Heavy-Polluting	(2) Non-Heavy-Polluting	(3) SOEs	(4) Non-SOEs
AI	−0.313 (0.266)	−0.325 (0.483)	−3.280 *** (0.846)	−0.395 (0.319)
AI ²	−0.213 (0.175)	−1.164 *** (0.246)	−4.700 *** (0.482)	−0.141 (0.164)
Constant	876.880 *** (9.330)	973.498 *** (19.969)	1004.849 *** (37.202)	935.701 *** (12.826)
Controls	YES	YES	YES	YES
Year	YES	YES	YES	YES
Firm	YES	YES	YES	YES
Observations	2569	7544	3502	6611
R-squared	0.053	0.074	0.115	0.041

Note: AI and AI² are mean-centered. Standard errors in parentheses, *** $p < 0.01$.

6.2. Firm Heterogeneity

To examine whether the effect of AI adoption intensity on GIA varies by ownership type, we divide the sample into state-owned enterprises (SOEs) and non-state-owned enterprises (non-SOEs). The results are reported in Table 13. The coefficient of AI² is significant for SOEs. SOEs possess more abundant R&D funding, technical talent, and data infrastructure, enabling AI to be deeply embedded in the entire green innovation process. When AI adoption intensity is moderate, its advantages can be fully leveraged to promote GIA. However, SOEs often have complex business processes and tightly coupled departmental structures. Excessive AI adoption can easily lead to path dependence, and adjusting AI models may affect the entire R&D system, thereby inhibiting GIA. In contrast, non-SOEs face more severe financing constraints and talent shortages, which prevent AI from delivering its full benefits. Therefore, the effect of AI adoption intensity on GIA is relatively weak for non-SOEs.

7. Conclusions and Discussion

7.1. Findings and Discussion

Artificial intelligence (AI) has emerged as a key enabler of green innovation. However, prior research has largely focused on aggregate green innovation outcomes or specific types of green innovation, with limited attention to the balance between exploratory and exploitative green innovation. Therefore, we draw on organizational ambidexterity theory and dynamic capabilities theory to examine the relationship between AI adoption intensity and green innovation ambidexterity (GIA), using data from Chinese A-share listed firms over the period 2011–2025. We further investigate how CEO IT background and CEO green experience moderate this relationship and whether CEO power shapes these moderating effects.

First, our findings reveal an inverted U-shaped relationship between AI adoption intensity and GIA, indicating that higher AI adoption intensity is associated with a more balanced relationship between exploratory and exploitative green innovation at lower levels but a less balanced relationship at higher levels. This finding supports the broader

double-edged sword perspective advanced by Zhang, Yang, Hu, Wang and Wu [48], Yin, Jiang and Niu [40] and Chen and Kahl [100], who highlight the coexistence of AI's enabling and inhibiting effects on innovation. We extend this perspective by showing that AI's implications for the balance of green innovation depend on adoption intensity, rather than merely identifying opposing effects on innovation outcomes. Our findings also extend Chen et al. [101], who report different associations between AI applications and green invention versus utility model patents, by shifting attention from individual innovation outputs to the balance between exploration and exploitation. More importantly, our results qualify research documenting AI's positive relationship with green technological innovation, such as Wang, Sun and Li [6], and challenge the inference that greater AI adoption necessarily improves green innovation ambidexterity. Rather than contradicting AI's potential to increase green innovation output, our study identifies an intensity-dependent boundary condition for its contribution to innovation balance. The distinctive contribution therefore lies in demonstrating that greater technological adoption is not necessarily associated with a more balanced green innovation portfolio.

Second, further analysis provides evidence consistent with dynamic capabilities as an intervening mechanism linking AI adoption intensity to GIA. Drawing on the dynamic capabilities perspective [60], moderate AI adoption may strengthen opportunity sensing, opportunity seizing, and resource integration by improving information processing, the evaluation of green innovation opportunities, and resource coordination. These capabilities may help firms pursue emerging green technologies while refining existing solutions, thereby balancing exploratory and exploitative innovation. At higher adoption intensities, however, implementation demands and excessive reliance on algorithmic outputs may divert managerial attention and constrain resource flexibility, undermining the capabilities needed to maintain this balance. Although these explanations require further investigation, the results suggest that dynamic capabilities should not be treated as an invariably increasing consequence of AI adoption. Instead, their nonlinear association with adoption intensity offers a potential explanation for AI's enabling and constraining effects on GIA. This finding extends the discussion beyond technological deployment itself by highlighting the organizational capabilities through which AI may shape the balance of green innovation.

Third, both CEO IT background and CEO green experience attenuate the inverted U-shaped relationship between AI adoption intensity and GIA. Consistent with upper echelons theory [102], this finding suggests that executive expertise shapes how technology adoption translates into green innovation outcomes. CEO's IT background may encourage more selective AI deployment by enabling a more informed assessment of technological benefits and implementation risks. Similarly, CEO green experience may provide environmental knowledge that partially substitutes for AI-generated insights in green innovation decisions. These interpretations suggest that managerial expertise can reshape, rather than merely amplify, the relationship between AI adoption and innovation balance. Our findings therefore complement research emphasizing the continuing importance of human judgment [103] and human–technology complementarity [104], including Huang and Chen [18] work on human–AI collaboration in green collaborative innovation. We extend this literature by identifying CEO expertise as a boundary condition for the nonlinear AI–GIA relationship, rather than merely an enabler of technology-driven innovation. Accordingly, firms should consider not only the intensity of AI adoption but also the managerial expertise that guides its deployment.

Fourth, CEO power attenuates the moderating effect of CEO IT background, suggesting that the influence of technical expertise depends on the concentration of decision authority. This finding is consistent with Sun, Zhang, Zhu, Mao and Liang [77] and

complements Zhang et al. [105], who document a power-related attenuation of the direct relationship between CEO environmental experience and green innovation. One plausible explanation is that greater power fosters overconfidence [106] and distorts investment judgments [107,108]. In the AI context, these tendencies may encourage CEOs to overestimate technological returns and underestimate implementation risks, thereby undermining the selective evaluation of AI deployment otherwise associated with IT expertise. By contrast, we find no significant evidence that CEO power shapes the moderating role of CEO green experience. Whereas IT expertise may operate through technology-specific assessments that are susceptible to power-related decision biases [77], green experience may shape more enduring environmental values and attentional priorities [109,110], potentially making its influence less sensitive to concentrated authority. This interpretation warrants caution, as the non-significant result neither rules out an influence of CEO power on the moderating role of green experience nor establishes a statistically significant difference between the two conditional effects. Overall, our findings extend the discussion beyond whether managerial expertise supports green innovation to how decision authority conditions its influence on the AI–GIA relationship. Our findings identify a governance boundary condition for CEO IT expertise while leaving the proposed cognitive mechanisms open to further investigation.

7.2. Theoretical Implications

First, whereas previous studies have examined exploratory and exploitative green innovation separately, this study focuses on the balance between them. Although existing studies have separately examined the differential effects of AI on exploratory and exploitative green innovation, the overall effect of AI on GIA remains insufficiently explored. Therefore, drawing on organizational ambidexterity theory, this study investigates the effect of AI adoption intensity on GIA. This extends ambidexterity theory to the green innovation context and offers a new perspective for future research on AI and GIA.

Second, drawing on dynamic capabilities theory, this study explains the relationship between AI adoption and GIA. Based on the three dimensions of dynamic capabilities—opportunity sensing, opportunity seizing, and resource reconfiguration—we systematically analyze how moderate versus excessive AI adoption intensity differentially affects dynamic capabilities. We identify the double-edged sword effect of AI adoption intensity on GIA and clarify the underlying mechanism through which AI reshapes organizational green innovation capabilities in the era of large models.

Third, by incorporating the moderating roles of CEO IT background and CEO green experience, we reveal the complementary and moderating effects of human factors in shaping the influence of AI technology. Prior studies have often emphasized the positive role of technology while overlooking human agency. By integrating CEO characteristics and AI adoption into a unified framework, this study enriches understanding of how human factors moderate the influence of AI technology.

7.3. Managerial Implications

First, firms should prioritize selective AI deployment over pursuing adoption intensity as an end in itself. The inverted U-shaped relationship between AI adoption intensity and GIA suggests that expanding AI use does not necessarily yield a more balanced green innovation portfolio. Managers should therefore adopt a phased approach, evaluating whether additional AI applications support both experimentation with new green technologies and improvements to existing products and processes. These assessments should track exploratory and exploitative activities separately rather than rely exclusively on aggregate green patent output or short-term efficiency gains. Regular portfolio reviews can inform

decisions to expand, redesign, or discontinue particular AI applications while protecting resources for exploratory projects. Importantly, the findings do not establish a universal optimal level of AI adoption. Deployment decisions should be tailored to firm-specific resources and industry conditions, and the subgroup results should not be interpreted as grounds for discouraging AI adoption in SOEs or heavy-polluting industries.

Second, boards should use executive expertise to improve the selectivity of AI-related decisions rather than assume that CEOs with technical or environmental expertise should pursue more extensive AI adoption. The moderating findings suggest that CEO backgrounds shape the relationship between AI deployment and innovation balance rather than uniformly amplify AI's benefits. CEOs with IT backgrounds can contribute to assessments of technological fit, data quality, and implementation risks, whereas those with green experience can help evaluate environmental relevance and competing green innovation priorities. Firms can bring these perspectives together through joint reviews involving IT, R&D, and sustainability functions. Where the CEO lacks either form of expertise, complementary knowledge within the management team or access to external specialist advice can support informed evaluation. Leadership development should therefore emphasize the integration of technological and environmental judgment rather than technical proficiency alone.

Finally, boards should complement executive expertise with independent scrutiny of major AI commitments. The finding that CEO power attenuates the moderating role of CEO IT background cautions against treating technical experience as a substitute for effective oversight. Separating project sponsorship from evaluation, requiring alternative deployment scenarios, and conducting post-implementation reviews can provide opportunities to challenge optimistic assumptions and reconsider underperforming applications. These safeguards should preserve executives' ability to pursue promising opportunities while ensuring that major commitments remain open to critical assessment. They should also apply across executive backgrounds, since the non-significant result for CEO green experience does not establish that such experience is unaffected by concentrated authority. The governance objective is thus to retain the value of managerial expertise without allowing decision concentration to displace the scrutiny needed to maintain a balanced green innovation portfolio.

7.4. Limitations and Future Research

Although this study examines the effect of AI on GIA, it has several limitations. First, we focus only on the effect of static AI adoption levels on GIA; however, dynamic dimensions, such as the speed and rhythm of AI adoption, may also shape GIA. Future research could therefore broaden the dimensions of AI adoption examined. Second, we measure green innovation using green patents, although alternative approaches such as textual analysis are also available. Future research could therefore develop more refined measures of green innovation. Third, this study focuses on the moderating role of CEO characteristics. However, other factors, such as firm resources, may also shape the AI–GIA relationship. Future research could therefore examine how moderators from other domains condition this relationship.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial intelligence
GIA	Green innovation ambidexterity
IT	CEO IT background
Green	CEO green experience
Power	CEO power
Size	Firm size
Lev	Leverage ratio
Top1	Shareholding ratio of the largest shareholder
State	Ownership nature
Growth	Firm growth
lnRD	R&D investment
Age	Firm age
DH	Board shareholding
DN	Board size

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