

Article

Navigating the Green Innovation Path: The Role of AI Adoption in Green Product and Green Process Innovation

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Abstract

In response to intensifying environmental pressures and the rapid pace of digital transformation, firms are increasingly turning to artificial intelligence (AI) as a tool to support sustainable development. Using panel data from Chinese A-share-listed manufacturing firms from 2016 to 2023, this study examines the relationship between AI adoption and two forms of green innovation: green product innovation and green process innovation. The results reveal that AI adoption is positively associated with both forms of green innovation, with a stronger association observed for green product innovation. The relationship between AI adoption and green innovation also varies across organizational and market contexts. CEO turnover weakens the association between AI adoption and green product innovation but strengthens its association with green process innovation. Market competition further strengthens the positive association between AI adoption and both types of green innovation. Further heterogeneity tests indicate that these associations tend to be more pronounced among high-tech firms and smaller firms. This study provides new evidence on the relationship between AI adoption and different forms of green innovation. It further clarifies the organizational and market conditions under which AI is more closely linked to corporate green transformation.

Keywords: Artificial Intelligence (AI); green product innovation (PROD); green process innovation (PROC); CEO turnover; market competition

1. Introduction

Against the backdrop of escalating environmental challenges and the growing importance of sustainable development, firms face the critical challenge of balancing economic performance with ecological responsibility [1,2]. In this context, green innovation represents an important strategy for firms to maintain long-term competitiveness while reducing environmental burdens. However, green innovation is typically associated with long development periods, high investment requirements, and significant uncertainty, which may undermine companies' motivation to continue pursuing green innovation. Therefore, stimulating and sustaining corporate green innovation necessitates a deeper understanding of its underlying drivers.

Simultaneously, artificial intelligence (AI), as a vital catalyst of digital transformation, is rapidly expanding from operational applications into domains with greater strategic and innovative orientation [3–5]. Its growing prevalence in corporate activities signifies that AI has become an important technological condition associated with corporate green transformation. However, although previous research has increasingly recognized the



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strategic significance of AI, the relationship between AI adoption and green innovation remains insufficiently understood.

A further complication is that green innovation is not a homogeneous construct. The term encompasses technologies, procedures, or systems designed to reduce environmental pollution and conserve energy and materials [6,7]. Prior studies suggest that green innovation falls broadly into two categories: green product innovation (PROD) versus green process innovation (PROC) [8,9]. It is essential to distinguish between these two forms, as they differ in terms of strategic orientation, resource requirements, and implementation logic [10,11]. Accordingly, a more specific question arises: whether AI adoption is associated with these two forms of green innovation in similar ways, or whether such associations are domain-specific.

Existing research has increasingly examined the connection between artificial intelligence and green innovation, with a prevailing consensus that AI may be closely linked to sustainable innovation within businesses. Scholars have further explored boundary conditions in this relationship, such as regulatory pressure [12], industry competition [13,14], and executive factors [15,16]. Nevertheless, there remain two significant limitations in the existing research. First, most existing studies treat green innovation as a homogeneous concept, failing to adequately account for the differences between the two types of green innovation. Consequently, it remains unclear whether AI adoption is associated with these two forms of green innovation in different ways. Second, although the moderating factors identified in previous studies are valuable for reference, insufficient consideration has been devoted to how internal governance dynamics and external competitive environments jointly condition the relationship between AI adoption and different categories of green innovation. These gaps limit our understanding of whether AI adoption is associated with different forms of green innovation and under what conditions such associations become stronger or weaker.

To address these issues, this study draws on dynamic capabilities theory as the overarching analytical lens [17,18]. Given that organizations need to coordinate multiple organizational functions when responding to environmental and technological changes, this study also incorporates a systems perspective, viewing the organization as a complex adaptive system [19]. Within this framework, AI is conceptualized as a tool of cybernetic management that may strengthen information processing, feedback, coordination, and adaptive control [20]. This systematically grounded explanation further clarifies the organizational mechanisms through which artificial intelligence supports green innovation. AI facilitates firms in transforming dispersed environmental, market, and operational information into feedback for product development and process improvement. CEO turnover and market competition are further conceived as two boundary conditions that shape the effectiveness of these AI-enabled adaptive mechanisms across different green innovation domains.

Within this framework, this study examines the association between AI adoption and two types of green innovation using data on Chinese A-share-listed manufacturing firms from 2016 to 2023. Concretely, this study employs annual report text analysis to extract the frequency of AI-related keywords and construct a firm-level AI adoption index. Further assessment of two types of green innovation is achieved through content analysis, and these metrics are combined with CEO turnover data and market competition indicators.

This study makes three main contributions. First, it distinguishes between green product innovation and green process innovation, thus yielding more detailed insights into the association between AI and different forms of green innovation. Second, this study broadens the scope of the theory of dynamic capabilities to encompass AI-driven green innovation, adopting a perspective that is grounded in systems analysis. Third, this study integrates CEO turnover and market competition within a cohesive analytical framework

and identifies the boundary conditions under which AI adoption is more closely associated with green innovation.

The subsequent sections of this document are organized accordingly. Section 2 develops theory and research hypotheses. Section 3 introduces the research design, data sources, variable assessments, and empirical models. Section 4 reports the empirical findings, including the baseline regressions, moderation analyses, robustness checks, endogeneity tests, and heterogeneity analyses. Section 5 concludes the paper and discusses practical implications and limitations.

2. Theory and Hypotheses

2.1. *AI and Two Types of Green Innovation*

2.1.1. Dynamic Capabilities Theory

Successfully navigating the green transition requires more than the adoption of new technologies. Companies need to identify emerging environmental demands, respond to evolving competitive and regulatory pressures, and continuously adapt their internal resources and organizational practices to support sustainability [21]. Green innovation is therefore inherently characterized by uncertainty, cross-functional coordination, as well as the need to balance environmental value creation with market competitiveness [22,23]. Dynamic capabilities theory offers a suitable framework for understanding how firms convert technological investments into green innovation-related outcomes. Rather than attributing competitive advantage solely to the possession of valuable resources, this theory emphasizes firms' capacity to sense opportunities and threats, seize emerging opportunities through strategic responses, along with restructuring internal and external resources to adapt to the changing environments [24].

The operation of dynamic capabilities is inherently systemic. Sensing, seizing, and reconfiguring do not occur within isolated organizational units. Instead, they depend on the continuous coordination of information and resources, including R&D, production, supply chain, and marketing. From this perspective, a firm can be viewed as a complex adaptive system in which organizational activities interact and adapt to changes in market, technological, and environmental demands [25]. This systemic characteristic is critical for green innovation, as the transition to sustainable development requires firms to align external environmental demands with internal product development, production processes, and environmental management practices.

In this systemic process, AI can support dynamic capabilities by functioning as a tool of cybernetic management. Cybernetic management emphasizes information processing, monitoring, feedback, coordination, and adaptive control [26]. These functions are closely related to the microfoundations of dynamic capabilities. First, AI may enhance sensing by helping firms identify environmental risks, market signals, and technological opportunities from dispersed internal and external data. Second, AI may support seizing by transforming complex information into actionable feedback for managerial decision-making, which helps firms evaluate alternative technological pathways and allocate resources more effectively. Third, AI may facilitate reconfiguring by improving coordination across organizational functions and supporting adjustments in product development, production processes, and environmental management routines.

This logic suggests that AI should not be viewed merely as a generic digital technology. Its strategic value depends on how firms embed AI-enabled information processing, feedback, and coordination into organizational routines that support green value creation and long-term competitive renewal [27]. When AI is integrated into dynamic capability processes, it helps firms transform fragmented environmental, market, and operational information into adaptive responses for green innovation [28,29]. However, these AI-enabled

capabilities may generate different outcomes across innovation domains. Green product innovation usually involves exploratory search, market demand, and knowledge integration, whereas green process innovation is more closely tied to existing production systems and operational efficiency. Therefore, distinguishing the two types of green innovation is necessary for understanding how AI contributes to different forms of green innovation.

2.1.2. AI and Green Product Innovation

Green product innovation entails the creation or modification of products in ways that reduce environmental hazards across the product life cycle while preserving or enhancing market value [30]. Previous research indicates that this form of innovation is far from limited to the launch of entirely new green products, but also encompasses improvements in product design, the use of sustainable materials, and enhancements in recyclability and durability [31]. In essence, green product innovation adopts a life-cycle perspective, targeting the alleviation of environmental burdens arising from production, utilization, disposal, reuse and recycling.

This form of innovation places particularly stringent demands on a company's ability to integrate environmental insights with product development. Recognizing the necessity for more eco-friendly products is inadequate. Companies must also determine which environmental attributes matter to customers, which technical solutions are feasible, and how to integrate these elements into commercially viable products [32]. This process relies on the firm's ability to integrate market, technical, and environmental knowledge across product development activities.

AI can enhance these capabilities in several ways. First, AI enhances a company's sensing capabilities by enabling it to interpret environmental signals within massive volumes of structured and unstructured data and uncover latent green demands. This helps firms identify product opportunities that might otherwise remain difficult to detect. Second, AI may strengthen a firm's ability to evaluate and act on such opportunities by supporting the screening of alternative materials, product designs, and technological pathways. It also accelerates the experimentation workflow, compressing timelines from concept generation to design selection [33]. Third, AI may support knowledge reconfiguration by facilitating the integration and reorganization of fragmented knowledge. This is particularly crucial for green product innovation, since eco-friendly products often depend on the effective coordination of customer value, technical feasibility, and ecological performance. In this sense, AI not only improves information efficiency but also helps firms transform fragmented knowledge inputs into viable green product solutions. Therefore, we propose a hypothesis:

H1a. *AI adoption is positively associated with green product innovation.*

2.1.3. AI and Green Process Innovation

Green process innovation entails refining production processes, operational procedures, and related technologies to alleviate the environmental footprint of manufacturing [34]. Existing research frames it as a proactive environmental governance strategy, implemented primarily throughout the manufacturing phase rather than subsequent to completion. More specifically, it encompasses reducing resource consumption, adopting clean manufacturing technologies and recycled materials, and incorporating pollution control or process support systems. Compared with green product innovation, green process innovation is more closely embedded in production activities because it focuses on improving the environmental efficiency of existing operational arrangements.

The implementation logic of green process innovation differs from that of green product innovation. The primary challenge lies not in identifying new market opportunities, but in diagnosing inefficiencies embedded within existing operations and translating those

observations into cleaner, more efficient production arrangements. Companies need to identify points of resource waste, sources of emissions, and components of the production system that can be adjusted without compromising production stability [35]. This requires tight coordination between analysis and execution, as well as aligning environmental goals with process control, equipment use, and workflow management practices. In other words, green process innovation depends to a greater extent on operational feasibility.

AI offers a distinct yet complementary pathway to support such innovation. First, through real-time monitoring of energy consumption, material usage, equipment status, and process bottlenecks, AI helps firms identify operational inefficiencies. This enables companies to detect environmental risks and operational losses with greater precision. Second, AI supports timely and data-driven insights in scheduling, process control, and resource allocation. These capabilities may help firms identify opportunities for cleaner production and process optimization. Third, AI can facilitate workflow redesign and adjustments to production logic, thereby integrating environmental goals more systematically into routine manufacturing decisions [36]. Through this approach, AI supports not only isolated process improvements but also more sustained, process-driven green upgrades.

In summary, AI enhances the potential for firms to transform operational data, process diagnostics, and environmental targets into more efficient and cleaner production outcomes. Therefore, this study proposes the following hypothesis:

H1b. *AI adoption is positively associated with green process innovation.*

2.1.4. Heterogeneity Across the Two Innovation Domains

The above analysis further suggests that the association between AI adoption and green innovation may differ across the two innovation domains. Although both are significant dimensions of green innovation and may interact in practice, previous research indicates that they diverge in their innovation priorities and implementation logic [37].

This distinction can be further understood from the perspective of firm adaptation. Green product innovation is more closely associated with external opportunity search and new knowledge recombination. It requires firms to interpret green market demand, respond to environmental requirements, and transform technological knowledge into new product attributes. These activities provide extensive opportunities for AI to support adaptive exploration and knowledge integration across organizational activities. Green process innovation also benefits from AI, but it is more closely tied to existing production systems. Process improvements typically require adjustments to equipment conditions, workflow scheduling, and operational practices. Therefore, while AI provides valuable diagnostic information, companies may still encounter stronger constraints when translating such information into actual process changes [38]. In light of the above analysis, we propose a hypothesis:

H1c. *The positive association between AI adoption and green product innovation is stronger than that between AI adoption and green process innovation.*

2.2. Hypotheses on Moderating Roles

The foregoing analysis suggests that the innovation value of AI is contingent rather than automatic [17]. This study conceptualizes CEO turnover and market competition as two boundary conditions that shape the relationship between AI adoption and the two types of innovation. CEO turnover signifies the internal governance stability required for capability coordination, while market competition reflects differences in external competitive pressure. Examining these two factors helps clarify the conditions under which AI adoption is more closely associated with green innovation.

2.2.1. The Moderating Role of CEO Turnover

CEO turnover represents a significant organizational event that reshapes leadership priorities, resource allocation, and strategic initiatives [39]. Previous research has established that inadequately structured succession processes frequently intensify the performance pressures experienced by newly appointed CEOs and exacerbate the cognitive limitations arising from a lack of familiarity with the company's unique resources [40]. Simultaneously, additional research indicates that CEO turnover can also catalyze the disruption of strategic inertia, prompting firms to abandon entrenched practices and direct attention toward new priorities [41]. These insights imply that CEO turnover may shape the relationship between AI adoption and green innovation differently across innovation domains.

For green product innovation, CEO turnover is likely to weaken the positive association between AI adoption and green product innovation. This pattern may be explained by the exploratory nature of green product innovation, as well as by the organizational continuity required for AI-related insights to be translated into tangible product outcomes [42]. While AI can enhance a company's ability to support environmentally oriented product development, these benefits only materialize when the company maintains stable strategic commitment, cumulative learning, and coordinated decision-making across organizational units. In practice, newly appointed CEOs need to quickly establish their legitimacy and demonstrate their competence, which may make them less willing to sustain initiatives that involve uncertainty and prolonged timelines [43]. Furthermore, CEO turnover may also interrupt ongoing learning processes, thereby undermining the consistency required to sustain AI-supported innovation efforts. Consequently, even when AI remains available as a technological capability, CEO turnover may reduce the extent to which AI adoption is associated with green product innovation. Given the above analysis, we hypothesize:

H2a. *CEO turnover negatively moderates the relationship between AI adoption and green product innovation.*

For green process innovation, CEO turnover may strengthen the positive association between AI adoption and green process innovation. Existing research suggests that CEO turnover may disrupt strategic continuity and increase organizational uncertainty. Yet little attention has been paid to whether leadership transitions also reshape the way companies leverage digital technologies in operational transformation [44,45]. This issue is particularly relevant in the context of AI adoption. Feedback produced by AI does not automatically lead to green process innovation. Its value depends on whether the CEO recognizes operational issues, allocates organizational resources, and supports changes to established production practices.

CEO turnover may facilitate this conversion process. Newly appointed CEOs may face pressure to demonstrate managerial effectiveness within a relatively short period. They may therefore focus more on improvements that are easier to observe and evaluate, such as efficiency enhancement, cost reduction, energy saving, and cleaner production [46]. Meanwhile, the new CEO, being less constrained by past management commitments, may be inclined to reassess existing production arrangements [47]. When AI provides diagnostic insights into operational inefficiencies, CEO turnover may increase the likelihood that such insights are used to justify process adjustments. Therefore, despite the potential for instability, CEO turnover may make companies more disposed to translate AI-based diagnostics into cleaner and more efficient production outcomes. Based on this, we propose the following hypothesis:

H2b. *CEO turnover positively moderates the relationship between AI adoption and green process innovation.*

2.2.2. The Moderating Role of Market Competition

Market competition constitutes not merely a contextual circumstance, but an external pressure that shapes firms' incentives to pursue strategic renewal, redeploy resources, and reconfigure organizational activities [48]. Intensified competition may increase uncertainty and short-term performance pressure, but it may also heighten firms' demand for differentiation and efficiency improvement. Existing research further indicates that competition may either suppress long-term capability investments or strengthen the conversion of strategic resources into breakthrough outcomes, depending on core innovation objectives and value realization mechanisms [49,50]. Overall, market competition acts as a conditional factor that shapes how AI-enabled capabilities are linked to green innovation outcomes.

This study argues that market competition strengthens the positive association between AI adoption and green product innovation. In fiercely competitive markets, firms experience heightened pressure to differentiate their products and adapt swiftly to evolving customer preferences. This pressure prevents companies from relying solely on existing product architectures or established market positions, thereby compelling them to pursue new opportunities for green products and overcome path-dependent innovation practices [51]. Simultaneously, intense competition compresses product lifecycles and magnifies the demand for immediate market insights alongside the rapid integration of technical and environmental knowledge [52]. Under these circumstances, AI emerges as particularly valuable, adept at processing fragmented information and integrating knowledge from customers, technology, and the environment into feasible product concepts [53]. Consequently, we propose a hypothesis:

H3a. *Market competition positively moderates the relationship between AI adoption and green product innovation.*

With respect to green process innovation, intense market competition may further strengthen the positive association between AI adoption and green process innovation. Distinct from green product innovation, competition operates more through operational discipline than through product differentiation. Amid intensifying competition, companies confront tighter cost constraints and an urgent imperative to enhance the efficiency and responsiveness of their production systems [54]. This external pressure may increase the value of AI in enabling real-time process visualization, identifying operational inefficiencies, improving energy utilization, and supporting more precise production control. Competition has also raised the cost of inefficiency, motivating firms to deploy AI in fields like process monitoring, predictive maintenance, and resource allocation [55]. From this perspective, market competition does not merely accelerate internal transformation within firms but rather intensifies the practical necessity of leveraging AI in support of cleaner, leaner, and more efficient production outcomes. Hence, we propose the hypothesis:

H3b. *Market competition positively moderates the relationship between AI adoption and green process innovation.*

Building on the above analysis, this study establishes a theoretical framework for the transmission mechanisms between AI and the two types of green innovation, as illustrated in Figure 1.

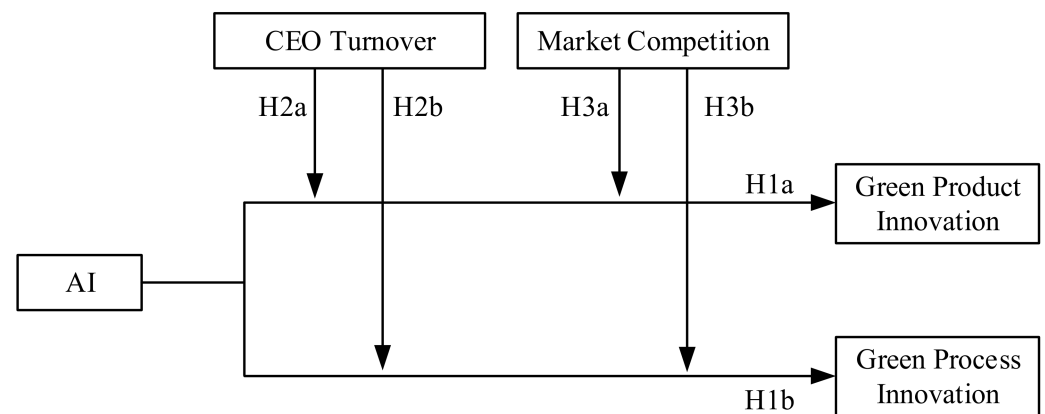


Figure 1. Transmission Mechanism Model from AI and Two Types of Green Innovation.

3. Econometric Model and Data

3.1. Sample Description

The sample covers manufacturing companies listed on the Chinese A-share market from 2016 to 2023. Manufacturing firms are selected because they are central to both AI applications and the green transition, while also confronting environmental and competitive pressures. Their annual reports, CSR reports, and financial and governance data are relatively comprehensive, which helps improve variable availability and sample comparability. We then exclude ST-designated firms and observations with missing key variables to enhance data quality and the reliability of the empirical analysis. The final sample includes 8645 firm-year observations.

The data are obtained from multiple authoritative sources. The CSMAR database provides financial and operational information on companies. Macroeconomic and industry data are obtained through the Wind Financial Terminal. The frequency data for AI-related terms are derived from text analysis of corporate annual reports. Two forms of green innovation were evaluated based on information disclosed in Corporate Social Responsibility Reports. Continuous variables are winsorized at the 1st and 99th percentiles to reduce the influence of outliers. This study employs Stata 18.0 and Python 3.8 for data processing.

3.2. Variable Measurement

3.2.1. Independent Variable

The independent variable is firm-level AI adoption, operationalized through an AI-related textual index derived from corporate annual reports. Following prior studies on AI innovation at the firm level and text-based measurement, this study constructs the index using Python-based text mining techniques [56–59]. The keyword dictionary is designed to capture three types of AI-related expressions: core AI technologies, AI methods, and clearly AI-based applications. Core AI technology terms include expressions such as “artificial intelligence”, “machine learning”, “deep learning”, “neural network”, and “natural language processing”. AI method-related terms include expressions such as “AI algorithm”, “algorithmic model”, and “intelligent algorithm”. AI-based application terms are retained only when the surrounding context clearly indicates the use of AI-related technologies. The frequencies of these AI-related terms are then aggregated at the firm-year level and transformed as $\ln(1 + \text{frequency})$. This index captures the extent to which firms incorporate AI-related technologies into strategic narratives and organizational activities. A higher value indicates stronger disclosed engagement with AI in operations, decision-making, and innovation activities.

3.2.2. Dependent Variables

Following Xie et al., this study employs a content-analysis method to assess two types of green innovation at the firm-year level based on firms' CSR reports [60]. To capture the essential dimensions of these two constructs more comprehensively, this study developed a set of systematic measurement indicators. Green process innovation is coded across five dimensions, including resource and energy reduction, adoption of recycling and cleaner process technologies, upgrading of equipment and production processes, green process planning systems, and environmental process R&D or pollution-control investment. Green product innovation is measured across four aspects, including the development of environmentally friendly products, eco-design improvements, green labels and packaging, and product recycling or take-back practices. Each item is coded on a three-point scale ranging from 0 to 2, where 0 indicates no relevant disclosure, 1 indicates general disclosure without specific implementation details, and 2 indicates substantive disclosure with detailed evidence. The final score for each construct is calculated as the average of the corresponding coded items. Detailed coding rules and examples are reported in Appendix B. To assess coding reliability, the two authors independently reviewed a randomly selected subsample of CSR reports using the same coding manual. The Krippendorff's alpha values for PROD and PROC were 0.789 and 0.827, respectively, indicating acceptable coding consistency.

3.2.3. Moderator Variables

Market competition captures the intensity of external competitive pressure faced by firms and is proxied by a competition indicator derived from the Herfindahl–Hirschman Index (HHI) at the industry-year level. Following prior studies that use the Herfindahl–Hirschman Index to measure industry competition [48,61], we first calculate HHI based on firms' sales shares within each industry-year. Specifically, the market competition variable is derived as follows:

$$HHI_{j,t} = \sum_{i=1}^{N_{j,t}} \left(\frac{Sales_{i,j,t}}{Sales_{j,t}} \right)^2 \quad (1)$$

$$MC_{i,t} = 1 - HHI_{j,t} \quad (2)$$

where $N_{j,t}$ denotes the number of firms in industry j in year t , $Sales_{i,j,t}$ is the sales revenue of firm i in industry j in year t , and $Sales_{j,t}$ is the total sales revenue of industry j in year t . Industries are classified according to the China Securities Regulatory Commission (CSRC) industry classification. Since HHI is calculated at the industry-year level, the market competition value assigned to each firm reflects the competitive environment of the industry to which it belongs in a given year. A higher HHI indicates that market shares are concentrated among fewer firms, suggesting a more concentrated market structure and weaker competitive pressure. To align the variable with the theoretical meaning of market competition, we reverse-code HHI to construct MC. Thus, a larger MC value reflects a more competitive industry environment faced by the firm in a given year [49].

In the context of Chinese listed firms, this study defines top executive turnover broadly as changes in either the board chair or the general manager. Given the structure of Chinese firms, these two roles collectively represent the company's executive leadership. The board chair is typically responsible for supervising the formulation of major strategic priorities and long-term resource allocation, while the general manager is more directly accountable for operational execution and routine management decisions. Considering that AI-driven green innovation thrives both on strategic coherence and implementation capacity, a change in either of these roles may reshape an enterprise's commitment to AI adoption and the trajectory of its green transition. CEO turnover is measured using a dummy variable that

takes the value of 1 if either the board chair or the general manager changes during a given year, and 0 otherwise [62].

3.2.4. Control Variables

This study includes a set of firm-level control variables to account for observable differences across firms that may be related to both AI adoption and green innovation. Firm size (Size), captured by the natural logarithm of total assets, reflects differences in corporate resource endowments and organizational innovation capacity. Financial leverage (Lev), expressed as the debt-to-assets ratio, captures financial pressure and debt constraints that may influence firms' engagement in green innovation. Fixed asset ratio (FA), calculated as fixed assets divided by total assets, accounts for differences in asset structure and production rigidity. Management expense ratio (MER) is defined as management expenses divided by total sales revenue and reflects management cost intensity and organizational efficiency. Firm age (Age), calculated as the natural logarithm of the number of years since establishment, captures accumulated experience, established routines, and organizational capabilities. Ownership concentration (Top1), represented by the equity stake of the largest shareholder, reflects the influence of controlling shareholders on strategic decision-making and long-term innovation incentives.

In addition, because the key variables in this study are constructed from corporate textual information, we further control for several disclosure-related factors. Annual report length (ARL), measured as the natural logarithm of one plus the total number of words in the annual report, is included to reduce the possibility that the AI measure is mechanically affected by the length of annual reports. CSR report length (CSRL), measured as the natural logarithm of one plus the total number of words in the CSR report, is included to account for differences in the amount of sustainability disclosure across firms. We also control for generic digital disclosure (Generic), measured as the natural logarithm of one plus the frequency of broad digitalization terms excluded from the refined AI dictionary. This control helps distinguish AI-related adoption from firms' general digitalization narratives. Table 1 describes the main variables, their symbols, and their measurements.

Table 1. Variable descriptions.

Variable Category	Symbol	Variables	Measurement
Dependent	PROD	Green product innovation	Measured using four content-analysis items based on CSR reports. Each item is coded on a 0–2 scale, and the average score is used.
Dependent	PROC	Green process innovation	Measured using five content-analysis items based on CSR reports. Each item is coded on a 0–2 scale, and the average score is used.
Independent	AI	Artificial Intelligence	Derived from the frequency of AI-related terms disclosed in annual reports and transformed as $\ln(1 + \text{frequency})$.
Moderating	Turnover	CEO turnover	A dummy variable equal to 1 if CEO turnover occurs in a given year, and 0 otherwise.
Moderating	MC	Market competition	Calculated as $1 - \text{HHI}$, where HHI is based on squared sales shares within each industry-year.
Control	Size	Firm size	Quantified as a natural logarithm of total assets
Control	Lev	Financial leverage	Calculated by the debt-to-asset ratio.
Control	FA	Fixed asset ratio	Computed by dividing fixed assets by total assets.
Control	MER	Management expense ratio	Calculated by dividing administrative expenses by total sales revenue.

Table 1. Cont.

Variable Category	Symbol	Variables	Measurement
Control	Age	Firm age	Measured as the natural logarithm of the number of years since establishment.
Control	Top1	Ownership concentration	Measured as the shareholding ratio of the largest shareholder.
Control	ARL	Annual report length	Natural logarithm of one plus the total number of words in the annual report.
Control	CSRL	CSR report length	Natural logarithm of one plus the total number of words in the CSR report.
Control	Generic	Generic digital disclosure	Natural logarithm of one plus the frequency of broad digitalization terms excluded from the refined AI dictionary.

3.3. Empirical Model Description

Using a two-way fixed-effects regression model, this study examines the association between AI adoption and the two types of green innovation. To reduce concerns related to time-invariant firm characteristics and common yearly shocks, we employ firm and year fixed effects. Firm-level fixed effects (μ_i) capture unobservable, time-invariant firm characteristics, such as organizational culture, management style, and other persistent attributes that may influence green innovation. Year fixed effects (λ_t) are used to control for unobservable shocks that vary over time but are common across firms, such as macroeconomic conditions, environmental regulations, and digital transformation policies. The benchmark model is formulated below:

$$\text{PROD}_{i,t} = \alpha_0 + \alpha_1 \text{AI}_{i,t} + \alpha_2 \text{Controls}_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (3)$$

$$\text{PROC}_{i,t} = \beta_0 + \beta_1 \text{AI}_{i,t} + \beta_2 \text{Controls}_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (4)$$

where $\text{PROD}_{i,t}$ indicates green product innovation by enterprise i at year t , and $\text{PROC}_{i,t}$ refers to the green process innovation by enterprise i at year t . $\text{AI}_{i,t}$ signifies AI adoption, while $\text{Controls}_{i,t}$ indicates control variables. $\varepsilon_{i,t}$ captures the idiosyncratic error term. We incorporate interaction terms into the baseline model to examine the moderating roles:

$$\text{PROD}_{i,t} = \alpha_0 + \alpha_1 \text{AI}_{i,t} + \alpha_2 \text{Moderator}_{i,t} + \alpha_3 \text{AI}_{i,t} \times \text{Moderator}_{i,t} + \alpha_4 \text{Controls}_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (5)$$

$$\text{PROC}_{i,t} = \beta_0 + \beta_1 \text{AI}_{i,t} + \beta_2 \text{Moderator}_{i,t} + \beta_3 \text{AI}_{i,t} \times \text{Moderator}_{i,t} + \beta_4 \text{Controls}_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (6)$$

where $\text{Moderator}_{i,t}$ is operationalized as CEO turnover when testing H2a and H2b, and as market competition when testing H3a and H3b. In the entire model, α_0 and β_0 are the constant terms, while i and t refer to the corporate and time dimensions.

4. Empirical Results

4.1. Descriptive Statistical Analysis

Table 2 summarizes the distributional characteristics of the main variables. The mean values of PROD and PROC are respectively 0.559 and 1.070, demonstrating that process-oriented green practices are disclosed more frequently than product-oriented ones in the sample firms. This pattern is plausible because green process innovation is more closely tied to routine production and cost management, which may make it easier for firms to implement and report. Conversely, green product innovation typically requires longer development cycles and involves greater technological uncertainty. The standard deviations of PROD and PROC, at 0.640 and 0.570, further suggest that firms differ considerably in their green innovation engagement. The mean value of AI is 0.642, with a standard deviation of 0.812, suggesting substantial variation in AI-related disclosure across firms. This variation

indicates that while a portion of firms have been more proactive in integrating AI into their strategies and operations, many others remain at an early stage of adoption. The mean CEO turnover rate is 0.094, indicating that CEO changes occur in a relatively small but non-negligible proportion of firm-year observations. Market competition (MC) has a mean of 0.818 and a standard deviation of 0.188, reflecting the variation in external competitive pressures among firms.

Table 2. Descriptive statistics.

Variables	Obs.	Mean	S.D.	Min	Max
PROD	8645	0.560	0.640	0.000	2.000
PROC	8645	1.070	0.569	0.000	2.000
AI	8645	0.642	0.812	0.000	5.000
Turnover	8645	0.094	0.292	0.000	1.000
MC	8645	0.818	0.188	0.036	1.000
Size	8645	22.724	1.379	17.668	29.155
Lev	8645	0.446	0.187	0.050	0.961
FA	8645	0.201	0.149	0.000	0.900
MER	8645	0.010	0.028	0.000	0.350
Age	8645	2.353	0.589	0.700	4.200
Top1	8645	0.338	0.145	0.046	0.800
ARL	8645	10.318	0.586	8.211	12.328
CSRL	8645	8.942	0.642	6.758	11.260
Generic	8645	0.786	0.874	0.000	5.000

Table 3 presents the Pearson correlation matrix. The correlation results provide preliminary evidence that is broadly consistent with the proposed associations. AI is positively correlated with both PROD and PROC, and both correlations are statistically significant at the 1% level. Specifically, the correlation between AI and PROD is 0.125, while the correlation between AI and PROC is 0.079. These results suggest that AI-related disclosure is positively associated with both types of green innovation disclosure, with a relatively stronger correlation for green product innovation. The correlation between PROD and PROC is 0.299, indicating that the two types of green innovation are related but still distinct. In addition, most correlations among the explanatory variables are moderate. The relatively high correlation between AI and Generic is 0.262, suggesting that AI-related disclosure is related to general digital disclosure. Furthermore, we also examined multicollinearity using variance inflation factors. The maximum VIF value is 1.375, which is well below the conventional threshold of 10, suggesting that multicollinearity is unlikely to be a serious concern.

Table 3. Correlation matrix.

Variables	PROD	PROC	AI	Turnover	MC	Size	Lev	FA	MER	Age	Top1	ARL	CSRL	Generic
PROD	1.000													
PROC	0.299 ***	1.000												
AI	0.125 ***	0.079 ***	1.000											
Turnover	−0.014	0.024 **	−0.005	1.000										
MC	0.022 **	0.019 *	−0.011	−0.010	1.000									
Size	0.043 ***	0.054 ***	−0.010	−0.001	−0.018 *	1.000								
Lev	−0.012	−0.018 *	−0.026 **	−0.018 *	−0.022 **	0.005	1.000							
FA	−0.022 **	−0.023 **	−0.002	0.006	−0.007	0.000	0.035 *	1.000						
MER	−0.008	−0.016	−0.000	0.017	−0.006	0.007	−0.011	0.016	1.000					
Age	0.028 ***	−0.013	0.003	0.002	0.002	0.012	0.006	0.001	−0.007	1.000				

Table 3. Cont.

Variables	PROD	PROC	AI	Turnover	MC	Size	Lev	FA	MER	Age	Top1	ARL	CSRL	Generic
Top1	0.002	0.024 **	−0.016	0.020 *	−0.025 **	0.015	0.020 *	−0.011	−0.014	0.014	1.000			
ARL	0.064 ***	0.086 ***	0.115 ***	0.002	−0.012	0.420 ***	−0.003	−0.021	0.002	−0.006	0.006	1.000		
CSRL	0.099 ***	0.123 ***	0.096 ***	−0.002	0.006	0.305 ***	−0.014	0.009	−0.016	0.004	0.019 *	0.369 **	1.000	
Generic	0.078 ***	0.059 ***	0.262 ***	0.000	−0.005	0.152 ***	−0.015	−0.007	−0.003	0.002	−0.003	0.275 **	0.222 ***	1.000

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.2. Baseline Regression

Table 4 reports the benchmark regression results. The coefficient on AI is positive and statistically significant in both the PROD and PROC regressions. After including fixed effects as well as a set of controls, the coefficient on AI is 0.0918 in the PROD model and 0.0476 in the PROC model, both significant at the 1% level. These results support H1a and H1b and indicate that AI adoption is positively associated with both forms of green innovation.

Table 4. Benchmark regression results.

Variables	PROD	PROD	PROC	PROC
AI	0.1037 *** (12.18)	0.0918 *** (11.34)	0.0569 *** (8.12)	0.0476 *** (6.89)
Size		0.0096 ** (1.97)		0.0061 (1.37)
Lev		−0.0234 (−0.70)		−0.0207 (−0.73)
FA		−0.0898 ** (−2.20)		−0.0985 *** (−2.65)
MER		−0.0655 (−0.31)		−0.0415 (−0.20)
Age		0.0464 *** (4.60)		−0.0065 (−0.69)
Top1		0.0072 (0.17)		0.0660 * (1.77)
ARL		0.0106 (0.90)		0.0282 ** (2.48)
CSRL		0.0743 *** (7.14)		0.0835 *** (8.88)
Generic		0.0063 (0.81)		0.0042 (0.64)
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	8645	8645	8645	8645
R ²	0.4072	0.4260	0.4115	0.4284

Notes: t -values are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

To examine whether this positive association differs between green product innovation and green process innovation, Table 5 reports a formal coefficient-difference test based on a stacked specification. The coefficient on AI captures its association with PROC, while the coefficient on the interaction term between AI and the product dummy captures the additional association with PROD. The results show that the difference in AI coefficients is positive and statistically significant, supporting H1c. This finding suggests that AI adoption is more strongly associated with green product innovation than with green process innovation.

Table 5. Coefficient difference test for H1c.

Variables	Difference Test
AI coefficient for PROC	0.0476 *** (6.89)
AI coefficient for PROD	0.0918 *** (11.34)
Difference in AI coefficients (AI $\times$ Product dummy)	0.0441 *** (4.15)
F-test for coefficient difference	17.24
<i>p</i> -value	0.000
Observations	17,290
Number of groups	1276
Controls	YES
Stacked fixed effects	YES
Year $\times$ innovation-type fixed effects	YES

Notes: *t*-values are reported in parentheses. The product dummy equals 1 for PROD and 0 for PROC. *** $p < 0.01$.

4.3. Moderating Roles

4.3.1. Moderating Role of CEO Turnover

Table 6 examines how CEO turnover conditions the association between AI adoption and the two forms of green innovation. In the PROD model, the coefficient for AI $\times$ CEO turnover is negative and statistically significant (-0.0728 , $p < 0.01$), suggesting that CEO turnover weakens the positive association between AI adoption and green product innovation. This result supports H2a. One possible explanation is that green product innovation often depends on long-term strategic continuity, cumulative technological learning, and sustained resource commitment, whereas CEO turnover may interrupt these conditions and reduce the extent to which AI-related activities are associated with green product innovation. In the PROC model, the coefficient of AI $\times$ Turnover is significantly positive (0.0677 , $p < 0.01$), suggesting that CEO turnover strengthens the positive association between AI adoption and green process innovation, thereby supporting H2b. This pattern is consistent with the view that green process innovation is more closely related to operational efficiency, cost reduction, and process optimization. After leadership changes, new CEOs may be more likely to emphasize efficiency adjustments, making AI-related activities more closely associated with green process improvements.

Table 6. Interaction results for CEO turnover.

Variables	PROD	PROC
AI	0.0980 *** (11.37)	0.0418 *** (5.81)
Turnover	0.0111 (0.42)	-0.0178 (-0.73)
AI $\times$ Turnover	-0.0728 *** (-2.83)	0.0677 *** (2.69)
Size	0.0095 * (1.95)	0.0062 (1.39)
Lev	-0.0250 (-0.75)	-0.0194 (-0.69)
FA	-0.0898 ** (-2.21)	-0.0984 *** (-2.66)
MER	-0.0671 (-0.31)	-0.0386 (-0.18)

Table 6. Cont.

Variables	PROD	PROC
Age	0.0464 *** (4.60)	−0.0065 (−0.69)
Top1	0.0098 (0.23)	0.0638 * (1.71)
ARL	0.0116 (0.98)	0.0273 ** (2.40)
CSRL	0.0741 *** (7.14)	0.0836 *** (8.90)
Generic	0.0061 (0.79)	0.0044 (0.68)
Firm FE	YES	YES
Year FE	YES	YES
Observations	8645	8645
R ²	0.4268	0.4292

Notes: *t*-values are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.3.2. Moderating Role of Market Competition

Table 7 extends the analysis to the external competitive environment by assessing the moderating role of market competition. The interaction term between AI and market competition is positive and statistically significant in both the PROD model (0.0883, $p < 0.05$) and the PROC model (0.0930, $p < 0.05$), supporting H3a and H3b. These results suggest that market competition strengthens the positive association between AI adoption and both forms of green innovation. This evidence is consistent with the argument that competitive pressure increases firms' incentives to deploy AI-related capabilities in support of green product differentiation and process-oriented environmental improvement. In this context, market competition can be understood as an external feedback mechanism that encourages firms to coordinate AI-enabled information processing with adaptive product and process adjustments.

Table 7. Interaction results for market competition.

Variables	PROD	PROC
AI	0.0925 *** (11.44)	0.0484 *** (7.03)
MC	0.0118 (0.30)	0.0061 (0.16)
AI × MC	0.0883 ** (2.21)	0.0930 ** (2.56)
Size	0.0098 ** (2.01)	0.0063 (1.41)
Lev	−0.0224 (−0.67)	−0.0198 (−0.70)
FA	−0.0909 ** (−2.23)	−0.0997 *** (−2.69)
MER	−0.0626 (−0.29)	−0.0383 (−0.18)
Age	0.0459 *** (4.56)	−0.0071 (−0.75)
Top1	0.0103 (0.24)	0.0692 * (1.85)
ARL	0.0107 (0.91)	0.0283 ** (2.49)

Table 7. Cont.

Variables	PROD	PROC
CSRL	0.0742 *** (7.14)	0.0834 *** (8.89)
Generic	0.0058 (0.76)	0.0038 (0.58)
Firm FE	YES	YES
Year FE	YES	YES
Observations	8645	8645
R ²	0.4267	0.4294

Notes: *t*-values are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.3.3. Comparison of Moderating Roles

Figure 2 visualizes the moderating roles of CEO turnover and market competition on the relationship between AI and the two forms of green innovation. In Panel A, the marginal association between AI adoption and green product innovation decreases from 0.0980 under CEO stability to 0.0252 under CEO turnover, whereas the corresponding association with green process innovation increases from 0.0418 to 0.1095. This pattern suggests that CEO turnover may weaken the continuity of strategic priorities, knowledge accumulation, and resource commitment required for AI adoption to be associated with green product innovation. At the same time, leadership change may shift managerial attention toward operational adjustment and efficiency improvement, thereby making AI adoption more closely associated with green process innovation.

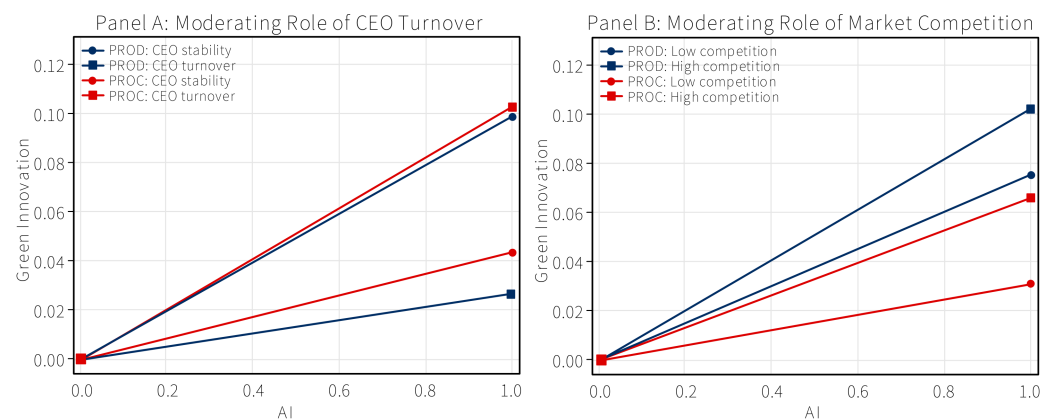


Figure 2. Slope chart of conditional associations. (**Panel A**) plots the association between AI adoption and two forms of green innovation under CEO stability (Turnover = 0) and CEO turnover (Turnover = 1), based on the interaction estimates described in Table 6. (**Panel B**) plots this association at low and high levels of market competition, where market competition (MC) is mean-centered for graphical presentation and evaluated at one standard deviation below and above the mean, according to the estimates presented in Table 7 and the descriptive statistics in Table 2.

In Panel B, market competition is centered around its mean, and the marginal associations are evaluated at one standard deviation below and above the mean. Under this specification, the marginal association between AI adoption and green product innovation increases from 0.0759 to 0.1091, while the corresponding association with green process innovation increases from 0.0309 to 0.0659. Taken together, these results suggest that CEO turnover changes how AI adoption is associated with different types of green innovation by reshaping managerial attention and resource coordination within the firm. In contrast, market competition reinforces the positive association between AI adoption and both

green product innovation and green process innovation by increasing external pressure for technological upgrading and environmental responsiveness.

4.4. Robustness Tests

To further examine the stability of the baseline findings, we conduct four robustness checks. The results are reported in Table 8.

Table 8. Robustness checks.

Variables	Purified AI		Alternative DV		Fractional probit		Industry-Year FE	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	PROD	PROC	PROD	PROC	PROD	PROC	PROD	PROC
AI_Pure	0.0687 *** (5.84)	0.0439 *** (4.26)						
AI			0.0758 *** (12.26)	0.0316 *** (4.34)	0.0408 *** (9.77)	0.0227 *** (5.61)	0.0903 *** (11.15)	0.0485 *** (7.12)
Size	0.0060 (1.22)	0.0043 (0.97)	0.0090 ** (2.51)	−0.0032 (−0.68)	0.0032 (1.17)	0.0019 (0.78)	0.0110 ** (2.26)	0.0056 (1.25)
Lev	−0.0310 (−0.92)	−0.0244 (−0.86)	0.0120 (0.52)	−0.0426 (−1.39)	−0.0113 (−0.61)	−0.0210 (−1.32)	−0.0221 (−0.66)	−0.0233 (−0.83)
FA	−0.0921 ** (−2.24)	−0.0998 *** (−2.68)	0.0035 (0.12)	0.0444 (1.18)	−0.0435 * (−1.96)	−0.0374 * (−1.84)	−0.0828 ** (−2.05)	−0.0906 ** (−2.44)
MER	−0.0739 (−0.35)	−0.0462 (−0.22)	−0.0514 (−0.34)	0.0431 (0.21)	−0.0711 (−0.57)	−0.1313 (−1.16)	−0.1104 (−0.52)	−0.0252 (−0.12)
Age	0.0483 *** (4.74)	−0.0055 (−0.58)	−0.0018 (−0.25)	−0.0164 * (−1.69)	0.0149 *** (2.61)	−0.0067 (−1.29)	0.0463 *** (4.64)	−0.0074 (−0.78)
Top1	−0.0073 (−0.17)	0.0582 (1.56)	0.0292 (0.94)	−0.0017 (−0.04)	0.0011 (0.04)	0.0412 ** (2.01)	0.0075 (0.18)	0.0749 ** (2.01)
ARL	0.0153 (1.29)	0.0303 *** (2.67)	−0.0085 (−0.99)	0.0133 (1.17)	0.0050 (0.74)	0.0167 *** (2.75)	0.0104 (0.88)	0.0281 ** (2.48)
CSRL	0.0775 *** (7.42)	0.0850 *** (9.03)	0.0005 (0.07)	0.0204 ** (2.00)	0.0362 *** (6.11)	0.0433 *** (8.37)	0.0759 *** (7.29)	0.0845 *** (9.04)
Generic	0.0205 *** (2.71)	0.0109 * (1.68)	0.0073 (1.27)	−0.0018 (−0.25)	0.0099 ** (2.50)	0.0034 (0.94)	0.0055 (0.72)	0.0045 (0.70)
Firm FE	YES	YES	YES	YES	NO	NO	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	NO	NO
Industry FE	NO	NO	NO	NO	YES	YES	NO	NO
Industry-year FE	NO	NO	NO	NO	NO	NO	YES	YES
Observations	8645	8645	8645	8645	8645	8645	8645	8645
R ² /Pseudo R ²	0.4181	0.4262	0.1668	0.1540	0.0179	0.0097	0.4351	0.4395

Notes: *t*-values are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

First, we replace the baseline AI measure with a purified AI index (AI_Pure). This index retains only purified AI technical terms, such as “artificial intelligence”, “machine learning”, “deep learning”, “neural network”, “natural language processing”, while excluding broader application-oriented or generic digitalization expressions. Columns (1) and (2) show that the coefficients remain positive and statistically significant for both green product innovation and green process innovation, suggesting that the baseline findings are not driven by broad digital disclosure.

Second, we use alternative measures of green innovation. In Column (3), green product innovation is alternatively measured by green patent applications, which provide externally observable evidence of green product technological activities. In Column (4), green process innovation is alternatively proxied by ISO14001 environmental management system certification, which reflects externally recognized environmental management and process improvement practices [63]. The results remain consistent with the baseline findings.

Third, we adopt fractional probit models as an alternative estimation method. Since the CSR-based green innovation scores are bounded between 0 and 2, we divide PROD and PROC by their maximum possible value to obtain bounded fractional scores in the range from 0 to 1 [64–66]. Columns (5) and (6) report the average marginal effects from the fractional probit models. The coefficients of AI remain positive and statistically significant, suggesting that the baseline associations are not sensitive to the use of a linear specification for bounded dependent variables.

Fourth, we include industry-year fixed effects to control for unobserved industry-level shocks that change over time. Because AI-related disclosure and green innovation may be jointly affected by industry-level conditions that vary over time, this specification helps absorb common shocks within each industry-year and provides a stricter test of the baseline association. Columns (7) and (8) show that the positive association between AI and green innovation remains statistically significant after replacing year fixed effects with industry-year fixed effects.

4.5. Endogeneity Test

Although the two-way fixed-effects model and robustness checks alleviate some endogeneity concerns, reverse causality may still remain if firms with stronger green innovation capabilities are also inclined to leverage AI. As a supplementary check, we use the industry-level average AI adoption (Industry AI), excluding the focal firm, as an instrumental variable. As shown in Table 9, the first-stage coefficient on the instrumental variable is positive and significant, and the first-stage F-statistic is 340.51, indicating that the instrument has strong explanatory power for AI adoption. In the second stage, the fitted value of AI remains positively associated with both PROD and PROC. The estimated coefficients are 0.0746 for PROD ($p < 0.05$) and 0.0709 for PROC ($p < 0.05$). These results are consistent with the benchmark findings and provide further support for the positive association between AI adoption and the two forms of green innovation. Given that industry-level AI adoption may also reflect common industry dynamics, regulatory environments, and disclosure practices, the IV estimates are interpreted as complementary evidence for the robustness of the baseline associations. Overall, the results suggest that the observed association between AI adoption and green innovation is unlikely to be driven solely by the baseline model specification.

Table 9. Instrumental-variable (2SLS) results.

Variables	2SLS—Stage 1	2SLS—Stage 2	
	AI	PROD	PROC
Industry AI	0.2979 *** (18.45)		
AI		0.0746 ** (2.18)	0.0709 ** (2.40)
Size	−0.0484 *** (−6.90)	0.0088 * (1.74)	0.0073 (1.55)
Lev	−0.1100 ** (−2.41)	−0.0253 (−0.75)	−0.0181 (−0.64)
FA	−0.0145 (−0.23)	−0.0900 ** (−2.18)	−0.0983 *** (−2.63)
MER	−0.0711 (−0.24)	−0.0666 (−0.31)	−0.0400 (−0.19)
Age	0.0051 (0.35)	0.0466 *** (4.57)	−0.0069 (−0.73)
Top1	−0.0992 (−1.57)	0.0049 (0.12)	0.0691 * (1.84)

Table 9. Cont.

Variables	2SLS—Stage 1	2SLS—Stage 2	
	AI	PROD	PROC
ARL	0.0822 *** (4.95)	0.0121 (0.98)	0.0262 ** (2.24)
CSRL	0.0451 *** (3.02)	0.0751 *** (7.12)	0.0823 *** (8.52)
Generic	0.2122 *** (17.41)	0.0101 (0.93)	−0.0010 (−0.11)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
First-stage F-statistic	340.51		
Observations	8645	8645	8645
R ²	0.2676	0.4159	0.4253

Notes: *t*-values are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.6. Heterogeneity Analysis

4.6.1. Heterogeneity Test by Technological Level

This study further examines whether the association between AI adoption and green innovation varies with firms' technological attributes. Based on the qualification recognition of high-tech firms, listed firms are divided into high-tech and non-high-tech groups, and group regressions are conducted. The results are shown in Table 10.

Table 10. Heterogeneity analysis by technological level.

Variables	PROD		PROC	
	High-Tech	Non-High-Tech	High-Tech	Non-High-Tech
AI	0.1192 *** (9.84)	0.0856 *** (5.51)	0.0715 *** (5.91)	0.0419 *** (3.36)
Size	0.0128 ** (2.30)	0.0022 (0.22)	0.0065 (1.29)	0.0047 (0.48)
Lev	−0.0037 (−0.10)	−0.1006 (−1.46)	−0.0107 (−0.32)	−0.0579 (−1.08)
FA	−0.0201 (−0.44)	−0.3147 *** (−3.58)	−0.0681 * (−1.66)	−0.1861 ** (−2.19)
MER	−0.2491 (−1.15)	0.6560 (1.01)	−0.0542 (−0.22)	0.0966 (0.21)
Age	0.0412 *** (3.64)	0.0672 *** (2.93)	−0.0109 (−1.00)	0.0048 (0.25)
Top1	0.0091 (0.19)	0.0321 (0.36)	0.0145 (0.33)	0.2409 *** (3.30)
ARL	0.0054 (0.40)	0.0231 (0.88)	0.0279 ** (2.17)	0.0322 (1.30)
CSRL	0.0826 *** (7.19)	0.0375 (1.56)	0.0919 *** (8.48)	0.0590 *** (3.10)
Generic	0.0055 (0.65)	0.0039 (0.21)	−0.0000 (−0.01)	0.0201 (1.29)
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	6705	1940	6705	1940
R ²	0.4028	0.3846	0.3957	0.3769
<i>p</i> -value of group difference	0.082		0.091	

Notes: *t*-values are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

AI adoption is positively and significantly associated with both green product innovation and green process innovation in the two subsamples. However, the coefficients are larger for high-tech firms. Specifically, for green product innovation, the coefficient of AI is 0.1192 in the high-tech group and 0.0856 in the non-high-tech group, with a group-difference *p*-value of 0.082. For green process innovation, the coefficient is 0.0715 for high-tech firms and 0.0419 for non-high-tech firms. These results provide suggestive evidence that the positive association between AI adoption and green innovation is stronger among high-tech firms. This pattern is consistent with the view that high-tech firms generally possess stronger technological capabilities, richer knowledge bases, and greater absorptive capacity. These characteristics may enable them to integrate AI-related information processing and knowledge recombination more effectively into green product development and green process innovation.

4.6.2. Heterogeneity Test by Firm Size

Firm size may influence the extent to which companies can translate AI into green innovation outcomes. Large firms typically possess more abundant resources and mature innovation ecosystems, which may facilitate the application of AI in green innovation. However, they may also face greater organizational inertia and more complex decision-making procedures. In contrast, small firms generally contend with tighter resource constraints. For these firms, AI adoption may help reduce information search costs and partially compensate for limited internal R&D resources.

To examine the heterogeneity, the sample is divided into large-firm and small-firm groups based on the median value of firm size, and separate regression analyses were performed for each group. As depicted in Table 11, AI adoption is positively and significantly associated with both types of green innovation in these two subsamples. However, the association is more pronounced among small firms, where the difference between the two groups is statistically significant. This pattern is consistent with the view that AI adoption may be particularly valuable for firms with relatively limited internal resources. For small firms, AI-related information processing and knowledge integration can partly substitute for resource-intensive search and coordination mechanisms, thereby helping them identify green innovation opportunities more efficiently.

Table 11. Heterogeneity analysis by firm size.

Variables	PROD		PROC	
	Large	Small	Large	Small
AI	0.0783 *** (5.96)	0.1046 *** (7.82)	0.0341 *** (3.12)	0.0587 *** (5.21)
Size	0.0134 (1.06)	0.0098 (0.85)	0.0176 (1.63)	0.0069 (0.64)
Lev	−0.1126 ** (−2.15)	0.0540 (1.02)	−0.0526 (−1.18)	−0.0107 (−0.25)
FA	−0.0910 (−1.45)	−0.0626 (−0.98)	−0.0774 (−1.36)	−0.0888 (−1.57)
MER	0.2585 (0.77)	−0.0499 (−0.14)	−0.1673 (−0.53)	0.1133 (0.33)
Age	0.0587 *** (3.60)	0.0442 *** (2.86)	−0.0014 (−0.10)	−0.0214 (−1.47)
Top1	0.0160 (0.24)	0.0708 (1.11)	−0.0103 (−0.17)	0.1449 ** (2.55)

Table 11. Cont.

Variables	PROD		PROC	
	Large	Small	Large	Small
ARL	−0.0071 (−0.39)	0.0368 * (1.95)	0.0148 (0.87)	0.0485 *** (2.78)
CSRL	0.0815 *** (4.94)	0.0705 *** (4.22)	0.0852 *** (5.59)	0.0810 *** (5.73)
Generic	−0.0012 (−0.11)	0.0072 (0.51)	−0.0068 (−0.70)	0.0258 ** (2.25)
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	4323	4322	4323	4322
R ²	0.3896	0.4018	0.3827	0.3942
<i>p</i> -value of group difference	0.087		0.092	

Notes: *t*-values are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5. Research Conclusions and Prospects

5.1. Conclusions

Existing research has increasingly recognized the innovation value of AI, yet its role in firms' green transformation remains insufficiently differentiated. In particular, insufficient attention has been paid to whether AI is associated with different domains of green innovation in the same way, and under what conditions these associations are amplified or diminished. Navigating the dual pressures of digital transformation and sustainable development, this study addresses these questions by examining the relationship between AI adoption and green product innovation and green process innovation, while further incorporating CEO turnover and market competition as boundary conditions into the analysis. Using panel data from Chinese A-share listed firms from 2016 to 2023 and a two-way fixed-effects model, this study provides a more nuanced understanding of how AI adoption is related to different forms of green innovation.

First, AI adoption is positively associated with the two types of green innovation. This finding suggests that AI may function as an important enabling capability for companies pursuing green transformation. It is linked not only to environmentally conscious product development but also to cleaner and more efficient process upgrades.

Second, the role of AI varies across the two types of green innovation. The positive association between AI adoption and green product innovation is stronger than that between AI adoption and green process innovation. This finding suggests that the value of AI depends on the nature of the innovation activities it supports. When core objectives focus more on information processing, opportunity identification, and knowledge integration, AI appears to be more closely associated with green innovation. However, when innovation outcomes remain narrowly tied to existing production conditions and implementation feasibility, the association is relatively weaker.

Third, CEO turnover conditions the relationship between AI adoption and the two green innovation domains through different organizational mechanisms. Specifically, CEO turnover weakens the positive association between AI adoption and green product innovation, as leadership changes often disrupt product development initiatives underway, reduce the continuity of long-term resource allocation, and undermine the cross-functional coordination required to advance AI-supported product endeavors. In contrast, CEO turnover strengthens the positive association between AI adoption and green process innovation, since new leadership tends to prioritize initiatives with clear operational

benefits, thereby facilitating the application of AI in process optimization and operational adjustment. This finding suggests that CEO turnover does not merely modify the general innovation outcomes of AI but rather conditions the domain in which AI adoption is more strongly associated with green innovation activities characterized by different time horizons and implementation logics.

Fourth, market competition serves as a positive moderating factor in the dynamic between AI adoption and both forms of green innovation. Facing heightened competition, firms encounter intensified pressure to update their products, improve efficiency, and adapt to evolving environmental and market demands. Consequently, AI adoption becomes more closely associated with green differentiation and cleaner production.

Fifth, the heterogeneity analyses suggest that the association between AI and green innovation varies across firm types. In particular, the estimated coefficients are generally larger for high-tech firms and for smaller firms, and the formal group-difference tests further support these heterogeneous patterns.

5.2. Practical Implications

The findings offer several implications for businesses, policymakers, and investors.

For businesses, AI should not be deployed as a generic digital tool. Instead, its use should be closely aligned with the specific domains of green innovation that firms seek to improve. When the objective is green product innovation, companies should place greater emphasis on applying AI to market insights, product design, and the integration of technical and customer knowledge. Should the focus shift to green process innovation, attention should be directed toward process monitoring, predictive maintenance, workflow optimization, and improvements in energy and material efficiency. Meanwhile, companies should recognize that the relationship between AI adoption and green innovation is contingent on governance and market conditions. Companies committed to strengthening green product innovation should maintain stable strategic commitment and persistent cross-functional coordination, while those pursuing process upgrades can leverage reorganization periods to accelerate AI-enabled operational improvements. Amid increasingly competitive markets, companies should proactively deploy AI to simultaneously support green differentiation and efficiency enhancements.

For policymakers, the results suggest that digital transformation policies and green development policies should be linked more closely. Instead of promoting AI adoption and green innovation as separate agendas, policy support should encourage their joint implementation through digital infrastructure development, data governance improvement, and targeted support for enterprise-level intelligent upgrading. In addition, because the association between AI adoption and green innovation varies across firms and innovation domains, policy design should remain differentiated, particularly with respect to firm size, technological capability, and competitive environment. More broadly, policymakers should support not only the diffusion of AI technologies, but also the organizational and institutional conditions that allow firms to use them effectively. This includes bolstering digital talent development, improving conditions for enterprise capacity building, and creating a policy environment that transforms AI into substantive green innovation rather than merely symbolic digital applications.

For investors, the findings imply that the evaluation of firms' AI strategies should move beyond simple technology adoption signals. AI-related disclosures, digital rhetoric, or announcements of intelligent transformation do not necessarily indicate that firms can generate substantive green innovation outcomes. Investors should pay closer attention to whether AI is being translated into concrete innovation activities, whether the resulting innovation is concentrated in green product innovation or green process innovation, and

whether the governance and market conditions are conducive to such translation. In particular, leadership stability, organizational coordination, and market pressure may shape the direction and strength of the association between AI adoption and green innovation. Investors can therefore improve their assessment of firms' long-term green growth potential by considering not only AI adoption itself, but also the organizational and environmental conditions under which AI is deployed. In this sense, AI should be evaluated as a contingent strategic capability rather than a standalone metric for innovation quality.

5.3. Limitations and Future Research

This study is subject to several constraints, which serve to identify avenues for future investigations.

First, the key variables in this study are constructed from textual and disclosure-based information. While this approach is appropriate for large-sample empirical analysis and allows us to capture firms' strategic attention to AI and green innovation, it may not fully reflect the depth and effectiveness of actual AI implementation. Such measures may also be affected by firms' disclosure practices, managerial incentives, and reporting preferences. Although this study conducts a series of robustness checks and endogeneity tests, some endogeneity concerns may remain. Accordingly, the empirical findings should be interpreted as conditional associations rather than definitive causal effects. Future research could improve measurement validity and strengthen causal identification by combining text-based indicators with more direct evidence, such as AI-related patents, digital investment, project-level AI applications, patent quality indicators, environmental certifications, environmental investment records, or field survey data.

Second, the sample is confined to Chinese A-share listed firms. Although this context is appropriate for examining AI-driven green transformation, the generalizability of the findings may still be constrained by China's regulatory environment, manufacturing structure, and the characteristics of listed firms. Future studies may extend the scope of analysis to non-listed firms, small firms, and firms in other economies.

Third, this study treats AI adoption in a relatively broad sense and does not differentiate among specific types of AI technologies. As AI continues to evolve, emerging forms such as generative AI and industry-specific intelligent systems may be associated with different innovation outcomes. Future research could therefore examine whether different AI technologies are associated with the two types of green innovation in distinct ways, and whether these associations extend to broader outcomes such as environmental performance and long-term competitive advantage.

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Appendix A. AI Keyword Dictionary and Index Construction Rules

Table A1. AI keyword dictionary and index construction rules.

Category	Keywords or Expressions	Coding Rule	Examples
Purified AI index	artificial intelligence; AI; machine learning; deep learning; neural network; natural language processing	Retained only when the expression explicitly refers to a core AI technology. Application-oriented AI expressions and broad digitalization terms are excluded.	Retained: “artificial intelligence platform”; “machine-learning-based quality inspection”; “neural network model for demand forecasting”.
Core AI technologies	artificial intelligence; AI; machine learning; deep learning; neural network; natural language processing; computer vision; image recognition; speech recognition	Retained when the expression clearly refers to artificial intelligence or a specific AI technology. Ambiguous abbreviations are retained only when the context indicates artificial intelligence.	Retained: “machine-learning-based quality inspection”; “natural language processing system”; “AI visual recognition platform”.
AI methods	AI algorithm; algorithmic model; intelligent algorithm; intelligent computing	Retained when the expression refers to AI-related methods, algorithmic intelligence, or AI-enabled analytical models. Generic uses of “algorithm” without AI-related context are excluded.	Retained: “AI algorithm for production scheduling”; “intelligent algorithmic decision-making”; “algorithmic model based on machine learning”. Excluded: “calculation algorithm” without AI context.
AI-based applications	intelligent recognition; intelligent decision-making; intelligent inspection; intelligent diagnosis	Retained when the surrounding context clearly indicates the use of AI technologies or AI-enabled systems. Application-oriented expressions are excluded when they refer only to general informatization or routine automation.	Retained: “intelligent inspection system based on computer vision”; “AI-based quality inspection”. Excluded: “intelligent office system” without AI context.

Appendix B. Coding Rules and Examples

Table A2. Coding rules for green product innovation.

Dimension	Coding Item	Score = 0	Score = 1	Score = 2
PROD1	Green product design	No product-related environmental disclosure	General mention of green or eco-friendly products	Specific product redesign, eco-design project, or measurable environmental improvement in product design
PROD2	Green materials	No disclosure on green or recyclable materials	General statement on using environmentally friendly materials	Specific replacement of materials, use of recyclable inputs, or reduction in hazardous substances
PROD3	Green packaging	No packaging-related environmental disclosure	General mention of green packaging	Specific recyclable, lightweight, degradable, or low-carbon packaging project
PROD4	Product life-cycle improvement	No life-cycle-related disclosure	General mention of reducing product environmental impact	Specific improvement in product energy efficiency, recyclability, durability, or end-of-life treatment

Table A3. Coding rules for green process innovation.

Dimension	Coding Item	Score = 0	Score = 1	Score = 2
PROC1	Cleaner production	No cleaner production disclosure	General mention of cleaner production	Specific cleaner production technology, project, or production-line improvement
PROC2	Energy-saving process	No energy-saving process disclosure	General statement on energy saving	Specific energy-saving equipment, process optimization, or energy-efficiency project
PROC3	Resource recycling	No resource recycling disclosure	General mention of recycling or reuse	Specific recycling, reuse, waste-heat recovery, or circular production system
PROC4	Pollution-control facilities	No pollution-control disclosure	General mention of pollution control	Specific wastewater, exhaust gas, dust, solid-waste, or noise-control facility
PROC5	Emission-reduction technology	No emission-reduction disclosure	General mention of emission reduction	Specific emission-reduction technology, investment, or quantitative reduction result

Table A4. Examples of coded items.

Example from CSR Disclosure	Coding Decision
The company attaches importance to environmental protection and actively promotes green development.	Not coded as green innovation because the statement is too general and does not describe a specific product or process innovation activity.
The company improved product packaging by using recyclable materials and reducing packaging weight.	Coded as green product innovation because the disclosure describes a specific product-related environmental improvement.
The company developed energy-saving products to reduce energy consumption during product use.	Coded as green product innovation because the disclosure refers to product energy-efficiency improvement.
The company introduced energy-saving equipment and optimized the production process to reduce electricity consumption.	Coded as green process innovation because the disclosure describes process upgrading and energy-saving production equipment.
The company upgraded wastewater treatment facilities and reduced pollutant emissions.	Coded as green process innovation because the disclosure refers to pollution-control facilities and emission reduction.

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