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A Literature Review on the Impact of Artificial Intelligence on Corporate Green Innovation

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Abstract

Against the backdrop of the deep integration of the digital economy and the green low-carbon transition, artificial intelligence (AI) has emerged as a critical technological force reshaping corporate innovation paradigms and facilitating sustainable development. Drawing on the authoritative literature in management, innovation management, and environmental economics, this study systematically reviews the conceptual foundations, research progress, and underlying mechanisms linking AI and corporate green innovation. The existing literature generally suggests that AI promotes green innovation through multiple pathways, including enhanced information processing, improved knowledge search, production optimization, the alleviation of financing constraints, more efficient resource allocation, and stronger organizational collaboration. However, the effectiveness of these mechanisms is contingent upon several contextual factors, such as firms' dynamic capabilities, green organizational culture, institutional environments, industry characteristics, and organizational attributes. Future studies should further distinguish among different forms of AI technologies, strengthen the examination of causal mechanisms, extend analyses to cross-country and multi-industry settings, and pay greater attention to the environmental costs associated with AI deployment as well as its long-term implications for substantive green innovation.

Keywords

Artificial Intelligence, Corporate Green Innovation, Influence Mechanisms

1. Introduction

Against the backdrop of deepening global climate governance, the increasingly stringent constraints imposed by China's dual-carbon goals, and the rapid restructuring of green trade rules, corporate green innovation is no longer merely a compliance tool for responding to environmental regulation. It has become a strategic means through which firms can build long-term competitive advantage, reshape value-creation logic, and pursue sustainable development. Climate change, resource constraints, and rising ecological risks have increased uncertainty in the external business environment, requiring firms to reconsider the environmental consequences of conventional innovation in energy use, pollution control, product design, and supply chain management. At the same time, ESG disclosure systems, green finance frameworks, emissions-trading mechanisms, and carbon-border measures have become more consequential for capital-market pricing, trade access, and stakeholder evaluation (Flammer, 2021). Whereas conventional innovation often prioritizes efficiency, cost reduction, and market competitiveness, green innovation also requires firms to pursue resource conservation, pollution reduction, and low-carbon transition through product, process, organizational, and business-model innovation (Chen et al., 2006).

From a management perspective, green innovation exhibits dual externalities. It can reduce environmental compliance costs, improve resource allocation efficiency, and strengthen market differentiation through energy conservation, cleaner production, green product development, and environmental management (Horbach, 2008). Yet green innovation is also associated with long investment horizons, high technological uncertainty, knowledge spillovers, and unstable short-term financial returns. Firms may therefore encounter insufficient resource commitment, coordination difficulties, and misaligned incentives when implementing green innovation initiatives (Rennings, 2000). Identifying the drivers of corporate green innovation, and explaining how firms convert external environmental pressure into internal innovation capability, remain central tasks in strategic management, innovation management, and environmental economics.

The rapid advancement of artificial intelligence (AI) has created new technological opportunities for overcoming the challenges associated with corporate green innovation. Unlike traditional information systems, which primarily focus on data recording, process standardization, and operational automation, AI leverages technologies such as machine learning, deep learning, natural language processing, computer vision, intelligent forecasting, and optimization algorithms to process unstructured data, generate multi-objective predictions, optimize dynamic decision making, and facilitate cross-domain knowledge discovery in complex environments (LeCun et al., 2015; Enholm et al., 2022). By identifying green technological opportunities, optimizing energy utilization, improving the precision of production process control, reducing the costs of environmental monitoring, enhancing supply chain collaboration, and strengthening managers' environmental decision-making capabilities, AI can significantly influence the intensity of green innovation investment, the quality of green innovation outputs, and the efficiency with which innovation outcomes are transformed into practical applications (Nishant et al., 2020).

Research has increasingly examined the relationship between AI and corporate green innovation. Early work often grouped AI with intelligent manufacturing, industrial robots, and broader digital technologies when assessing green patents, technological innovation, or innovation efficiency. Although both direct AI studies and adjacent-technology studies commonly report positive associations, only studies that explicitly operationalize AI can support an AI-specific inference; industrial-robot evidence, for example, is treated here as comparative rather than direct evidence (Liang et al., 2023). Subsequent AI-focused research has examined technological capability, innovation investment, financing frictions, information transparency, and executive orientation as explanatory channels (Wang et al., 2024), while ownership, firm size, pollution intensity, institutional conditions, and analyst scrutiny have emerged as boundary conditions (Hussain et al., 2024).

Although research on AI and corporate green innovation has expanded rapidly, the field remains at an early stage of theoretical integration. Three limitations are particularly important. First, construct boundaries remain inconsistent because some studies treat industrial robots, intelligent manufacturing, digital transformation, or big data adoption as proxies for AI. Second, the explanatory mechanisms remain fragmented and lack theoretical integration. Existing studies have examined mediating pathways from various perspectives, including information processing efficiency, knowledge spillovers, green dynamic capabilities, the alleviation of financing constraints, and organizational culture alignment. However, the relative importance of these mechanisms and their potential interactions have not been systematically evaluated or theoretically synthesized. Third, causal identification remains relatively weak because many studies rely on cross-sectional data or conventional observational regressions. These problems reduce the comparability, causal credibility, and cumulative value of the evidence.

Building on this practical background and the identified research gaps, this study provides a structured narrative review and critical assessment of representative research on AI and corporate green innovation. It addresses three questions: How are AI and corporate green innovation defined and bounded? What does the literature show about the direct effects, mediating mechanisms, and moderating mechanisms through which AI relates to corporate green innovation? Which limitations in the current evidence base should guide future research?

This study adopts a structured narrative review approach to synthesize the literature on the relationship between artificial intelligence and corporate green innovation. To improve methodological transparency, the review scope, search strategy, and study selection criteria are explicitly specified. This study searched Web of Science Core Collection, Scopus, and CNKI for studies published up to December 2025. The search terms combined focal AI-related keywords, including "artificial intelligence", "AI", "AI adoption", "machine learning", and "intelligent algorithm", with green-innovation-related terms such as "green innovation", "eco-innovation", "environmental innovation", "green patent", and "green technology innovation", together with firm-level identifiers such as "firm", "enterprise", and "corporate". Studies were included when they examined or enabled theory building around the effects of AI or closely related intelligent digital technologies on corporate green innovation outcomes, mechanisms, or boundary conditions. Studies were excluded when they focused only on macro-level green growth, general informatization without an intelligent-technology core, or lacked a clear research design and variable definition. Given the heterogeneity of samples, measures, and identification strategies across the literature, this paper does not conduct a meta-analysis; it develops a thematic synthesis and comparative interpretation of the evidence.

The academic contributions of this study are threefold. First, it clarifies the conceptual boundaries among AI, adjacent digital technologies, and green innovation, thereby improving the comparability of the reviewed evidence. Second, it integrates research on direct effects, mediating mechanisms, moderating mechanisms, and measurement choices into a common explanatory framework. Third, it identifies limitations in construct validity, causal identification, and external validity, providing a focused agenda for management research on how AI may enable corporate green transformation.

The remainder of this paper is organized as follows. Section 2 reviews the conceptual evolution and definitions of AI and green innovation. Section 3 synthesizes AI research, green innovation research, direct, mediating mechanisms, and moderating mechanisms. Section 4 summarizes the main findings, evaluates limitations and controversies, and develops directions for future research and practice.

2. Conceptual Evolution of Artificial Intelligence and Green Innovation

2.1. Concepts Related to Artificial Intelligence

Artificial intelligence is a multifaceted concept that integrates elements of computer science, information systems, organizational management, and innovation studies. Owing to differences in research objectives, levels of analysis, and disciplinary perspectives, the existing literature has not yet reached a fully unified definition of artificial intelligence. Early research primarily emphasized the simulation of human cognitive functions, using algorithms and computational systems to perform tasks such as reasoning, recognition, learning, and decision-making. With the rapid advancement of machine learning, deep learning, natural language processing, and intelligent control technologies, AI has increasingly been understood as a technological system capable of continuous learning, prediction, and optimization based on data. Within the fields of management and organizational studies, it is further viewed as an organizational capability embedded in strategic decision-making, production operations, knowledge search, resource allocation, and innovation activities. Definitions of artificial intelligence proposed by different scholars are summarized in Table 1.

In this paper, artificial intelligence (AI) refers to machine-based systems that, for explicit or implicit objectives, infer from the input they receive how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments. This definition emphasizes inferential capability rather than the broad use of digital tools. Accordingly, AI should be conceptually distinguished from adjacent constructs. Digital transformation refers to organization-wide reconfiguration enabled by digital technologies (Vial, 2021), whereas big data analytics capability concerns an organization's capacity to collect, integrate, analyze, and exploit data (Mikalef et al., 2020). Industrial robots are embodied forms of programmable automation (Liang et al., 2023), and intelligent manufacturing is a system-level production paradigm that may integrate AI with robotics, the industrial internet, sensing infrastructure, and data platforms. AI may therefore be a component of digital transformation or intelligent manufacturing, but it is not synonymous with either construct.

Table 1. Definitions of artificial intelligence by different scholars.

Scholars	Definitions related to artificial intelligence
Cockburn et al. (2018)	Artificial intelligence is regarded as a general-purpose technology with broad applicability, capable of reducing the costs of knowledge discovery, research automation, and technology development.
Kaplan & Haenlein (2019)	Artificial intelligence is the ability of a system to correctly interpret external data, learn from that data, and achieve specific goals and tasks through flexible adaptation.
Dwivedi et al. (2021)	Artificial intelligence comprises technologies capable of perception, comprehension, action, and learning, whose organizational use also raises managerial, policy, ethical, and societal questions.
Mariani et al. (2022)	In the context of innovation research, artificial intelligence is viewed as a composite technological system capable of supporting knowledge search, idea generation, product development, and organizational innovation processes.
Enholm et al. (2022)	Artificial intelligence is not merely a technological tool. It is an organizational capability that can be embedded into organizational processes, transforming how enterprises make decisions, operate, and create value.
Wang et al. (2024)	Artificial intelligence is a comprehensive technical capability through which enterprises utilize algorithmic models, data resources, intelligent devices, and automated decision-making systems to perceive, recognize, learn from, predict, optimize, and provide feedback on information, while embedding these capabilities into processes such as R&D and design, production and operations, resource allocation, supply chain collaboration, and environmental management.

2.2. Concepts Related to Green Innovation

Green innovation did not emerge as an isolated concept. It developed through related streams on environmental innovation, eco-innovation, and sustainable innovation. Environmental innovation emphasizes reductions in pollution, energy consumption, and resource waste through technological change and is closely associated with cleaner production, end-of-pipe treatment, and environmental technologies. Eco-innovation has a broader scope, covering systematic reductions in ecological burdens across products, processes, supply chains, organizational arrangements, and business models. Sustainable innovation extends the boundary further by integrating economic, environmental, and social objectives. In this review, corporate green innovation refers to new or significantly improved products, processes, organizational practices, or business models that reduce environmental burdens while contributing to value creation. Table 2 summarizes representative definitions and conceptualizations.

Table 2. Definitions of green innovation by different scholars.

Scholars	Definitions related to green innovation
Rennings (2000)	Eco-innovation is understood as innovation activities at the technological, organizational, social, and institutional levels that can reduce environmental impact, with the shared goal of mitigating that impact.
Chen et al. (2006)	Green innovation is categorized into green product innovation and green process innovation, emphasizing improvements in the environmental attributes of products and the green transformation of production processes, respectively.
Kemp & Pearson (2007)	Eco-innovation is defined as the development and application of new products, processes, services, or management methods that reduce environmental risks, pollution, and resource use.
Schiederig et al. (2012)	The terms green, eco/ecological, and environmental innovation are used largely synonymously for innovations that reduce environmental harm, whereas sustainable innovation is broader because it also incorporates a social dimension.
Waqas et al. (2021)	Green innovation is treated as firm-level product and process innovation through which big data analytics capability can be translated into competitive advantage and improved environmental performance.
Dong et al. (2025)	Green innovation requires distinguishing between two levels: quantitative expansion and qualitative improvement.

3. Current Status of Research

3.1. Research Related to Artificial Intelligence

Research on artificial intelligence has not evolved along a single linear trajectory. Instead, it has progressively expanded through the intersection of multiple disciplines, including computer science, information systems, strategic management, organizational behavior, and innovation management. While research priorities have varied across different stages, these efforts have collectively driven the evolution of artificial intelligence from a mere computational technology into a significant management topic that influences organizational decision-making, business processes, innovation models, and value creation.

1) Organizational adoption and managerial application of artificial intelligence. As AI has entered operations, marketing, finance, human resources, supply chain management, and customer service, research has shifted toward how organiza-

tions adopt, integrate, and govern these technologies. Dwivedi et al. (2021) argued that AI is not merely a collection of technologies capable of perception, comprehension, action, and learning; its organizational use also raises managerial, regulatory, ethical, and societal questions. The business value of AI therefore does not arise automatically from implementation. It depends on complementary organizational structures, data infrastructure, managerial capabilities, employee competencies, institutional arrangements, and governance mechanisms.

2) The reshaping of organizational decision-making and value-creation processes by artificial intelligence. As AI becomes more deeply embedded in organizations, it increasingly participates in strategic analysis, resource allocation, risk identification, process optimization, and business-model innovation rather than functioning only as a supporting information system. Brynjolfsson and McAfee (2017) emphasized that AI and related digital technologies are transforming productivity, the division of labor, and corporate competition. Raisch and Krakowski (2021) further described an automation-augmentation paradox: AI can substitute for standardized and repetitive tasks while augmenting human judgment, creativity, and collaboration.

3) The integration of artificial intelligence and innovation management. As AI is increasingly applied to R&D design, knowledge search, product development, and idea generation, innovation management research has begun to examine how it changes the organization of innovation. Mariani et al. (2022) found that AI can support knowledge search, opportunity recognition, idea generation, product development, and organizational learning. Enholm et al. (2022) further argued that realizing business value from AI depends not only on algorithms but also on complementary resources, including data governance, organizational processes, employee capabilities, and strategic alignment.

4) The rise of research on generative AI and AI governance. Large language models, generative AI, and agent-based systems have extended AI research from analytical and predictive applications to content generation, knowledge collaboration, complex reasoning, and human-AI co-creation (Floridi & Chiriatti, 2020). These technologies can improve efficiency in text generation, coding, design, knowledge-intensive services, and solution planning, but they also raise concerns about algorithmic bias, data security, intellectual property, accountability, job displacement, and organizational control (Raisch & Krakowski, 2021).

3.2. Research on Green Innovation

3.2.1. Measurement of Corporate Green Innovation

Corporate green innovation is measured in at least four ways across the reviewed studies. The first and most common approach uses green patents, including patent applications, grants, or green invention patents specifically, as indicators of technological output (Zhang & Chen, 2023). The second approach focuses on green innovation efficiency, which captures the degree to which firms convert innovation inputs into environmentally oriented technological outcomes (Wang et al., 2024; Feng et al., 2024). The third approach examines green process innovation through cleaner production practices, energy-saving process upgrades, or improvements in environmental management systems (Chen et al., 2006; Aftab et al., 2022). The fourth approach adopts broader outcome-oriented indicators, such as environmental performance scores or green ESG ratings, to reflect the realized effects of a firm's green innovation capability (Long et al., 2023; Yang et al., 2024). Because these measures capture different dimensions of the underlying construct: technological invention, efficiency, process upgrading, and environmental outcomes, the findings across studies are not always directly comparable.

3.2.2. Antecedents of Green Innovation

The antecedents of green innovation are typically classified into two dimensions: internal firm-level drivers and external institutional factors. Research on internal drivers draws mainly on the resource-based view. R&D investment is regarded as a direct resource base for corporate green innovation. Higher R&D investment can help firms build capabilities in clean technology, energy conservation and emissions reduction, and green product development. R&D activities can increase green technology output and may strengthen firms' long-term competitive advantage by generating technological accumulation and knowledge spillovers (Bataineh et al., 2023).

In addition to technological and capability factors, organizational and human resource factors also serve as important internal drivers of green innovation. Aftab et al. (2022) found that green human resource management practices, including green training, environmental performance appraisal, and green incentive mechanisms, significantly enhance firms' green innovation performance. Management's environmental commitment and organizational learning capability are also regarded as important intangible drivers of green innovation. Top managers' environmental orientation shapes firms' strategic choices. It also indirectly affects green innovation output through institutional design and resource allocation (Ahmed et al., 2023).

Regarding external drivers, the literature has examined institutional pressure, market mechanisms, and policy environments. Environmental regulation and policy incentives alter the cost-benefit structure of innovation by increasing pollution costs, setting performance standards, or providing green subsidies. Chang et al. (2024) found that green finance policy improves the green innovation performance of heavily polluting firms, illustrating how financial institutions and public policy can redirect resources and strengthen innovation incentives.

ESG evaluation systems and stakeholder pressure are also important external influences on corporate green innovation. Long et al. (2023) reported a significant association between ESG performance and green innovation, although the relationship is not necessarily linear. Stronger ESG pressure may induce firms to invest in green innovation to satisfy evaluators and stakeholders, but it may also encourage selective disclosure or symbolic environmental practices when incentives emphasize observable ratings rather than substantive outcomes (Yang et al., 2024). Corporate social responsibility mechanisms can similarly affect reputation, competitiveness, and innovation incentives. Padilla-Lozano and Collazzo (2022) linked corporate social responsibility and green innovation to manufacturing competitiveness, reinforcing the strategic rather than purely compliance-based interpretation of green innovation.

3.2.3. Economic and Environmental Consequences of Green Innovation

Research on the consequences of green innovation has mainly focused on four outcomes: improved environmental performance, enhanced competitive advantage, stronger organizational performance, and reduced carbon emissions. Studies in this area generally report positive associations, although the magnitude, mechanisms, boundary conditions, and causal interpretation vary across studies.

From the perspective of environmental performance, green innovation is widely regarded as a mechanism for reducing pollution and improving resource efficiency. Aftab et al. (2022) showed that green innovation mediates the relationship between green human resource management and environmental performance, translating management practices into environmental improvements. Ahmed et al. (2023) further found that green innovation not only improves environmental performance but also enhances organizational performance. This occurs by improving resource utilization efficiency and strengthening process optimization capability.

From the perspective of corporate competitive advantage, green innovation has increasingly been recognized as a critical source of competitive differentiation. Waqas et al. (2021) examined green innovation within a framework linking big data capability, competitive advantage, and environmental performance. They found that green innovation is both an outcome of firms' accumulated digital capability and a key driver of competitive advantage.

Green innovation also plays a significant role in shaping macro-level performance and carbon emission outcomes. Chen and Jin (2023) studied carbon emissions in the manufacturing sector and found that green innovation, through technological improvement and process optimization, reduces the energy consumption and environmental burden associated with AI application. Green innovation is therefore not only a direct determinant of environmental performance but may also serve as a buffering and optimization mechanism through which emerging technologies influence environmental outcomes.

3.3. The Direct Impact of Artificial Intelligence on Corporate Green Innovation

Evidence Based on Explicit AI Constructs

Early representative studies primarily focused on the overall effects of artificial intelligence, while also beginning to incorporate multidimensional analytical frameworks. Wang et al. (2025) systematically examined the impact of AI on corporate green innovation across four dimensions: direct effects, indirect effects, spatial spillover effects, and heterogeneous effects. Their research not only confirmed that artificial intelligence significantly promotes green innovation among local firms but also revealed that this effect generates spillovers through mechanisms of industrial linkages and regional technology diffusion. Zhong and Song (2025) argued that the adoption of AI not only directly influences green innovation output but also strengthens the foundation of a firm's long-term green innovation capabilities by enhancing knowledge integration, technological learning, and organizational adaptability.

As data availability has improved and identification strategies have advanced, recent studies have begun to examine more directly which types of green innovation artificial intelligence promotes. Using a sample of Chinese energy firms, Wang et al. (2024) found that AI significantly improves green total factor innovation efficiency. Dong et al. (2025) further examined whether AI simultaneously increases both the quantity and quality of green innovation. They found that AI increases the volume of green patent output. It may also improve green innovation quality by optimizing R&D pathways and reshaping knowledge combinations. However, these two effects are not fully symmetric.

A group of studies examines technologies that are related to AI but analytically distinct. Industrial-robot adoption has been associated with higher corporate green innovation in Chinese manufacturing firms (Liang et al., 2023; Liu et al., 2025). Big data applications and analytics capabilities have been linked to factor allocation, green innovation, competitive advantage, and environmental performance (Gao et al., 2023; Waqas et al., 2021). Digital transformation has also been connected to green innovation through changes in financing modes and organizational processes (Zhang et al., 2024). These findings corroborate information-processing, automation, and resource-allocation channels that may also operate under AI. They should not, however, be used as direct estimates of an AI effect because robots, digital transformation, big data capability, and intelligent manufacturing differ from AI in technological content, organizational scope, and measurement.

3.4. Research on the Mediating Mechanisms of Artificial Intelligence's Impact on Green Innovation

As a general-purpose technology, artificial intelligence does not affect green innovation through a simple input-output relationship. Instead, its influence operates through pathways embedded in firms' information processing systems, resource allocation structures, financing conditions, and organizational capabilities and culture. These pathways together form a multidimensional set of mediating mechanisms.

First, the information processing capabilities and knowledge search mechanism. Artificial intelligence leverages machine learning, natural language processing, and data mining technologies to process and integrate large volumes of heterogeneous data from both internal and external sources. These data include corporate annual reports, patent databases, production and operational records, supply chain transaction data, and environmental monitoring information. By transforming complex data into actionable knowledge, artificial intelligence substantially reduces the cost of searching for green technologies and enhances firms' ability to identify green innovation opportunities (Mariani et al., 2022).

Second, the resource allocation efficiency and production process optimization mechanism. Artificial intelligence, big data analytics, and industrial robotics enhance corporate green innovation by optimizing production processes, improving equipment operating efficiency, and strengthening the allocation of production factors. These technologies reduce resource waste and energy consumption throughout the production process, thereby creating favorable conditions for green innovation (Gao et al., 2023). On the production side, artificial intelligence improves production accuracy, lowers defect rates, and reduces energy consumption, enabling firms to achieve greener process improvements and advance process innovation toward more sustainable production practices (Liu et al., 2025).

Third, the financing constraint alleviation mechanism. Green innovation is typically characterized by long investment cycles, high risk and uncertainty, and significant externalities, making it susceptible to financing constraints. Artificial intelligence and related digital technologies can alleviate these constraints by enhancing corporate information transparency and improving firms' risk assessment capabilities, thereby providing the financial support required for green innovation (Zhang et al., 2024). Song et al. (2025) further linked artificial intelligence, digital finance, and green innovation, demonstrating that the synergistic development of intelligent technologies and financial technology enhances firms' access to external finance and improves capital allocation efficiency, which in turn increases both green innovation investment and innovation output.

Fourth, green capability reconfiguration and organizational culture mechanisms. The application of artificial intelligence does not automatically translate into green innovation outcomes; its actual impact depends heavily on whether an enterprise possesses the corresponding strategic orientation, organizational capabilities, and cultural environment. Artificial intelligence contributes to organizational environmental performance by fostering green innovation capabilities and reinforcing green organizational culture, with internal values and behavioral norms serving as critical mediating mechanisms (Lin et al., 2024). Furthermore, Zhong and Song (2025) found that AI adoption is often accompanied by a systematic reconfiguration of firms' green innovation capabilities, including stronger knowledge integration, enhanced cross-functional collaboration, and improved dynamic learning capabilities.

3.5. Moderating Mechanisms and Boundary Conditions

Existing research generally suggests that the relationship between AI and corporate green innovation is not uniformly positive across contexts. Its magnitude, and in some cases its direction, depends on internal capabilities, organizational culture, external institutions, industry conditions, and firm characteristics.

First, the moderating role of dynamic capabilities. Feng et al. (2024) found that dynamic capabilities significantly moderate the relationship between artificial intelligence and corporate green innovation efficiency, particularly through firms' capabilities in data governance, cross-functional collaboration, and technology absorption. Firms with weak dynamic capabilities are unlikely to fully leverage artificial intelligence to enhance green innovation. Although AI adoption may improve specific operational processes, it is insufficient to generate systematic improvements in firms' green innovation capabilities.

Second, the moderating role of green culture. Lin et al. (2024) argued that green culture plays a pivotal moderating role in the relationship between artificial intelligence and green innovation. In firms with a weak green culture, artificial intelligence is more likely to be prioritized for enhancing production efficiency or expanding production capacity, rather than for pollution control or the research and development of clean technologies.

Third, the moderating role of the external institutional environment and policies. In terms of artificial intelligence policy, Mijit et al. (2025) and Lin and Zhu (2025), based on evidence from AI innovation pilot zones and AI policy shocks, found that policy support significantly enhances both firms' intensity of AI adoption and the resulting green innovation outputs. This indicates that institutional technology policies influence not only the speed of AI diffusion but also the efficiency of its translation into green innovation. Chang et al. (2024) argued that green finance policies indirectly moderate the efficiency with which AI technological capabilities are converted into green innovation outputs. In regions with a higher level of green finance development, AI-driven green innovation is more likely to receive complementary support from capital markets.

Fourth, the moderating role of industry characteristics and pollution attributes. It has received substantial empirical attention in recent years, yet the findings remain mixed. On the one hand, some studies suggest that heavily polluting and energy-intensive industries, which face more direct emission-reduction pressures, are more likely to adopt AI technologies to improve pollution control efficiency and thereby enhance green innovation (Li & Chen, 2025). On the other hand, industry characteristics may also generate a rebound effect. In high energy-consuming sectors, the computational demand and equipment expansion driven by AI can increase overall energy consumption, which may in turn weaken green innovation outcomes (Mhlanga, 2025).

Fifth, firm heterogeneity and the moderating role of regional digital infrastructure. In general, large enterprises and publicly listed firms, due to their stronger data accumulation capabilities, capital advantages, and technological absorptive capacity, are more likely to transform artificial intelligence into green innovation outcomes (Li et al., 2024). In contrast, small and medium-sized enterprises and non-listed firms may struggle to fully realize the green innovation potential of artificial intelligence because of high AI adoption costs, talent shortages, and financing constraints (Crocco et al., 2025).

Taken together, the reviewed studies suggest that the effect of AI on corporate green innovation can be synthesized into a sequential explanatory logic rather than a set of isolated channels. The first mechanism is knowledge creation: AI enhances information processing, opportunity recognition, and the recombination of technical knowledge, thereby strengthening green technology innovation capability. The second mechanism is resource reallocation: AI improves decision quality, relaxes financing constraints, and channels organizational resources toward more innovation-intensive and sustainability-oriented uses. The third mechanism is organizational implementation: AI-enabled environmental management, process optimization, and cross-functional coordination increase the likelihood that green ideas are translated into actual innovation outputs. Knowledge creation and resource reallocation receive comparatively stronger support, while organizational implementation serves as an important transmission and amplification mechanism.

4. Conclusions, Limitations, and Future Research

This study systematically reviews the existing research on artificial intelligence and corporate green innovation. The evidence generally indicates positive relationships with green patenting, green innovation efficiency, and green product or process innovation, but the interpretation depends on whether studies measure AI itself or adjacent digital technologies. The reviewed mechanisms can be organized into an integrated logic in which AI strengthens information processing and knowledge search, improves project and production-resource allocation, may reduce financing frictions, and supports the reconfiguration of green capabilities. Dynamic capabilities, green culture, institutional arrangements, industry conditions, and firm characteristics shape whether these potential advantages are converted into substantive innovation outcomes.

4.1. Limitations and Controversies in the Existing Evidence

The most immediate limitation concerns construct validity. Many archival studies infer AI adoption from annual-report keyword frequencies, AI-related patent counts, regional pilot policies, robot deployment, or broad digital transformation indices. These proxies enable large-sample analysis but may capture managerial disclosure, automation, or digital intensity rather than the depth and purpose of actual AI use. Survey measures provide richer information about use cases but introduce respondent and common-method biases. Triangulating disclosure measures with AI investment, system logs, project-level use, workforce data, and survey evidence would improve construct validity.

Causal identification and external validity are also limited. A substantial share of the literature relies on cross-sectional surveys or observational panel regressions, leaving reverse causality and omitted organizational capability difficult to rule out. Quasi-natural experiments and policy-based difference-in-differences designs are emerging, but they remain a minority and often use policy exposure rather than realized firm-level AI use. Moreover, the empirical evidence is heavily concentrated in Chinese A-share listed firms, particularly manufacturing, energy, and heavily polluting industries (Hussain et al., 2024; Wang et al., 2024; Feng et al., 2024). This concentration limits generalization to small and medium-sized enterprises, unlisted firms, service sectors, and institutional settings with different data, finance, environmental regulation, and innovation regimes. Finally, outcome heterogeneity across patent counts, efficiency indices, survey scales, and environmental performance complicates comparison and may contribute to selective reporting of positive results.

4.2. Research Gaps and Future Directions

Future research can be extended in three directions. First, future studies should adopt a more fine grained classification of artificial intelligence by distinguishing among AI for research and development, AI for intelligent manufacturing, AI for supply chain management, AI for environmental monitoring, and generative AI. This approach would help identify the heterogeneous effects of different AI application scenarios on green innovation. Second, research should move beyond single indicators such as the number of green patents. Greater attention should be paid to the quality of green innovation, technological complexity, breakthrough innovation, and actual environmental performance. This shift would strengthen the explanatory power of research findings. Finally, future studies should strengthen causal identification and the analysis of micro-level mechanisms. Quasi-natural experiments, multi-source heterogeneous data, and machine learning methods can be used to systematically examine how AI shapes the process of corporate green innovation. In addition, the energy consumption, carbon footprint, and potential rebound effects associated with intelligent manufacturing itself should be incorporated into the analytical framework. Such efforts would enable a more comprehensive assessment of the net environmental value of artificial intelligence.

4.3. Managerial and Policy Implications

At the practical level, firms should not treat AI as a one-time technology acquisition or equipment upgrade. AI should be integrated with green strategy, R&D management, production transformation, data governance, and environmental management, while performance systems should track both innovation outputs and net environmental effects. The green innovation potential of AI is more likely to be realized when technological capability, dynamic capability, and green culture develop together. Public policy should likewise coordinate AI industrial policy, green finance, digital infrastructure, and environmental regulation. Pilot programs, targeted finance, tax incentives, and skills development can lower adoption barriers for small and medium-sized enterprises, while disclosure standards should require reliable information on AI-related energy use, carbon emissions, green patent quality, and realized environmental performance. Such safeguards can reduce the risk that increases in reported innovation obscure weak substantive environmental benefits.

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Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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