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How Artificial Intelligence Empowers Green Supply Chain Management: From the Perspective of Firm Internal Capabilities

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Abstract： As the core driving force of the new generation of industrial revolution, artificial intelligence technology has brought new opportunities for empowering enterprise green transformation and advancing sustainability. Focusing on Chinese A-share listed companies and based on unbalanced panel data from 2016 to 2024, this study systematically examines the impact, transmission mechanisms, and heterogeneity of AI applications on green supply chain management (GSCM). Drawing on the resource-based view and dynamic capabilities theory, this paper constructs an integrated theoretical framework that traces a causal link between AI applications through firm internal capabilities to green supply chain management. The empirical results show that AI applications significantly promote GSCM. Mechanism tests reveal that AI indirectly enhances GSCM by improving four dimensions of firm internal capabilities: green innovation, ESG performance, supply chain efficiency, and resource integration. In addition, heterogeneity analysis indicates that the enabling effect of AI on GSCM is more pronounced in state-owned enterprises, firms with higher environmental information disclosure quality, and firms in heavily polluting industries. This study deepens theoretical understanding of the relationship between AI and GSCM, reveals the micro-mechanisms and boundary conditions of AI-enabled GSCM, and provides practical insights for policymakers to guide firms in strategically applying AI and building efficient and collaborative green supply chains.

Keywords: artificial intelligence; green supply chain management; green innovation; ESG performance; firm internal capabilities

1. Introduction

Against the backdrop of accelerating global sustainable development agendas, Green Supply Chain Management (GSCM) has become a core strategy for reshaping the business ecosystem and achieving economic-environmental synergy. In recent years, international regulation of supply chain environmental responsibilities has become increasingly stringent. New types of regulations, represented by the EU's Corporate Sustainability Due Diligence Directive (CSDDD) issued in 2024, extend sustainability requirements concerning the environment and human rights to global business activities and associated supply chains in a calculated and strategic manner, posing new compliance challenges for companies across nations (Liu et al., 2025; Mao, 2022)[1][2]. This directive requires companies to conduct due diligence on potential environmental and human rights risks within their supply chains, an impact that transcends traditional trade barriers and serves as a crucial driver of global supply chain restructuring (Liu et al., 2025; Afifi et al., 2026)[3][4]. Concurrently, international academic interest in GSCM continues to intensify, with research perspectives continuously expanding and deepening. Related bibliometric analysis finds that research in this field is evolving from a single environmental dimension towards a systematic framework integrating the Triple Bottom Line of

Economy, Society, and Environment, with GSCM practices, closed-loop systems, and ethical considerations becoming core themes (Mohsin et al., 2025)[5].

Domestically, the Chinese government places high importance on the sustainable development of supply chains. Since 2014, policy formulation has accelerated significantly, with a series of guiding policies successively issued, including the Industrial Green Development Plan (2016-2020), the Green Manufacturing Project Implementation Guide (2016-2020), and the Guiding Opinions of the General Office of the State Council on Actively Promoting Supply Chain Innovation and Application. In 2017, the Guiding Opinions of the General Office of the State Council on Actively Promoting Supply Chain Innovation and Application clarified the key industries and main links for developing green supply chains. In 2018, eight ministries including the Ministry of Commerce jointly issued the Notice on Carrying out Pilot Projects for Supply Chain Innovation and Application, making GSCM a core component of the pilots and emphasizing a green development orientation throughout the entire process, chain, and links. In 2019, the Outline Development Plan for the Guangdong-Hong Kong-Macao Greater Bay Area further proposed promoting the development of green supply chains. In 2020, China officially proposed the "carbon peaking and carbon neutrality" strategic goals, elevating green and low-carbon development to a national strategic height. The same year, the newly revised Law on the Prevention and Control of Solid Waste Pollution came into effect, providing legal support for advancing GSCM through legal means. In 2021, the 14th Five-Year Plan for Circular Economy Development issued by the National Development and Reform Commission explicitly proposed building a resource-circulating industrial system and implementing GSCM. That same year, the 14th Five-Year Plan for Industrial Green Development issued by the Ministry of Industry and Information Technology further emphasized building green supply chains and cultivating green supply chain management enterprises. In 2022, the Notice on Improving Industrial Quality and Brand Building for 2022 issued by the General Office of the Ministry of Industry and Information Technology called for guiding enterprises to establish GSCM systems. In 2023, the Opinions on Accelerating the Establishment of a Product Carbon Footprint Management System jointly issued by the National Development and Reform Commission and other departments provided technical guidance for the quantitative assessment of GSCM. In 2024, the Opinions on Accelerating the Comprehensive Green Transformation of Economic and Social Development issued by the Central Committee of the Communist Party of China and the State Council explicitly called for promoting the green and low-carbon transformation of upstream and downstream enterprises in supply chains through means such as innovation and technological application. The successive introduction of these policies has collectively built the institutional framework for GSCM in China, demonstrating the firm determination of the state to promote industrial green upgrading (Tian et al., 2024)[6].

Despite the improving policy environment, corporate GSCM practices in China still commonly face a paradox of high policy enthusiasm but low implementation efficiency (Liu et al., 2025; Mao, 2022)[7][8]. Existing research reveals that the direct impact of environmental regulations on GSCM is often insignificant, with their effect requiring transformation through internal factors such as entrepreneurship and circular-oriented resource commitment (Liu et al., 2025)[7]. In the process of advancing GSCM, enterprises often face practical difficulties such as information asymmetry, resource constraints, cost pressures, and poor coordination among supply chain partners (Ren et al., 2023; Xue et al., 2023; Rodríguez-Escoto et al., 2025)[9][10][11]. The adoption of digital traceability technologies is still in its early stages, with internal organizational commitment and marketing strategies explaining adoption behavior better than external pressures, revealing the crucial role of internal driving forces in

GSCM transformation (Muller et al., 2026)[12]. How to combine external regulatory pressure with internal technological capabilities and transform them into systematic green management actions has become a challenge urgently needing resolution in both theory and practice. Existing research mostly focuses on the antecedents and consequences of GSCM, such as driving factors (Tian et al., 2024; Stendel et al., 2026)[6][13], performance impacts (Xie & Zhu, 2022; Wang et al., 2024; Sharma et al., 2026)[14][15][16], and spillover effects (Bu et al., 2025; Yan et al., 2024; Han et al., 2025)[17][18][19]. However, there is a lack of in-depth exploration into the "black box" mechanism of how GSCM is effectively activated within complex organizations, particularly when external technological shocks reconstruct internal capabilities.

In the digital intelligence era, new generation digital technologies represented by artificial intelligence (AI) offer new possibilities to address these challenges. With its powerful capabilities in data perception, intelligent decision-making, and system optimization, AI is profoundly reshaping the operational logic of supply chain management (Shi et al., 2025; Yang & Liu, 2024)[20][21]. Research shows that AI technology can significantly enhance supply chain efficiency by improving the precision of supply-demand matching, reducing transaction costs, and optimizing logistics scheduling (Zhang, 2022; Meng & Hu, 2025; Zhang et al., 2025; Babaei et al., 2025)[22][23][24][25], and provides new opportunities for enhancing supply chain transparency and traceability (Bytyqi et al., 2026)[26]. In the field of green transformation, AI demonstrates multi-dimensional enabling potential: firstly, AI can promote corporate green technology innovation, driving disruptive green innovation by enhancing the breadth and depth of knowledge search (Zhou et al., 2025; Chen et al., 2025)[27][28]; secondly, AI applications can help improve corporate ESG performance by enhancing the level of green technology innovation, increasing information transparency, and optimizing resource allocation (Xu et al., 2024; Tang et al., 2025; Lin & Huang, 2026)[29][30][31]; thirdly, AI can optimize supply chain efficiency and resource integration capabilities, laying an operational foundation for GSCM by enhancing total factor productivity (He & Guo, 2026; Jin et al., 2025; Qi & Cheng, 2025; Albulescu et al., 2025)[32][33][34][35]. Furthermore, AI plays an instrumental and strategic role in shaping supply chain resilience, driving transitions through adaptive, continuous, and transformative resilience via human-machine collaboration (Song et al., 2024; Lyu et al., 2026; Zhang et al., 2026)[36][37][38]. From a supply chain network perspective, the application of AI by core firms also has knowledge spillover effects, promoting innovation and collaboration among upstream and downstream partners (Guan & Zheng, 2026; Li et al., 2026)[39][40].

Consequently, international academic research at the intersection of AI and sustainable supply chains is rapidly emerging. A study on the Indian tea industry shows that AI-driven collaborative models can significantly improve supply chain coordination, predictive analytics, and automation processes, thereby enhancing operational efficiency, profitability, and sustainability, providing a scalable model for the intelligent transformation of agricultural supply chains (Paul et al., 2025)[41]. Research targeting the automotive manufacturing industry finds that AI-driven circular supply chains have become a key support for enterprises adopting circular economy practices, with strategic initiatives such as "AI-enabled infrastructure configuration" and "robotics-driven manufacturing and material reclamation" being the most important (Sharma et al., 2026)[16]. A systematic review of healthcare supply chains reveals that technologies such as AI, digital twins, and the Internet of Things are evolving from efficiency tools into strategic enablers of decision intelligence, supporting real-time sensing, scenario analysis, and proactive risk mitigation. This "triple integration of digital transformation, resilience, and sustainability" is emerging as a core trend in global supply chain

development (Thiyagarajan et al., 2026)[42]. The agentic AI framework demonstrates how sustained learning can continuously optimize procurement, logistics, and inventory decisions, significantly reducing costs while decreasing carbon emissions (Aylak, 2025)[43]. An extension of the Technology Acceptance Model reveals that retailers' intention to use AI for product waste reduction is primarily driven by perceived economic utility, knowledge level, and perceived usefulness, providing a micro-foundation for understanding AI adoption in supply chain green practices (Mouloudj et al., 2026)[44]. In the circular supply chain domain, scholars have explored how AI can enhance the adoption of closed-loop supply chains through digital strategies (Sharma et al., 2026)[16], and how the synergistic application of technologies like blockchain and the Internet of Things with AI can enhance supply chain sustainability (Abdallah-Ou-Moussa et al., 2026; Ruggieri et al., 2026)[45][46]. Additionally, the role of AI in supply chain risk management and resilience building has garnered significant attention, with research indicating that AI can enhance supply chain robustness and velocity (Yamin et al., 2026)[47], and improve the ability to cope with uncertainty by optimizing resource allocation and building dynamic capabilities (Babaei et al., 2025; Bag, 2025)[25][48].

Despite the above studies exploring the economic and environmental effects of AI from various perspectives, systematic research on how digital technology enables sustainable supply chain management remains insufficient (Liu et al., 2025; Cichosz et al., 2025; Rocío González-Sánchez et al., 2025)[1][49][50]. Most existing literature treats AI as an exogenous shock or direct driver, with few studies delving into the chain transmission mechanism through which AI influences GSCM by enhancing firm internal capabilities. Furthermore, whether the impact of AI on GSCM exhibits heterogeneity concerning firm attributes and industry characteristics also requires further testing. Based on this, this paper attempts to answer the following core questions: Can AI promote corporate GSCM? What are its pathways of action? Do differences exist in this impact across different firm characteristics?

The potential contributions of this paper are as follows: First, it constructs an integrated theoretical framework that traces a causal link between AI applications through firm internal capabilities to green supply chain management, breaking through the limitations of existing research focusing solely on direct technological effects and systematically revealing the micro-mechanisms through which AI empowers corporate green sustainable development. Second, based on panel data of Chinese A-share listed companies from 2016 to 2024, it employs various econometric methods to provide reliable empirical evidence for understanding the relationship between digital technology and organizational green transformation. Third, it conducts heterogeneity analysis from perspectives such as ownership nature, environmental information disclosure quality, and industry pollution attributes, identifying the boundary conditions for the enabling effect and offering references for policymakers to implement differentiated guidance strategies. This paper not only deepens the theoretical understanding of the relationship between digital technology and organizational green transformation but also provides practical insights for policymakers to guide enterprises in precisely applying AI and building efficient and collaborative green supply chains.

2. Theoretical analysis and research hypotheses

2.1 Artificial Intelligence and Green Supply Chain Management

Green supply chain management (GSCM), as an innovative environmental management approach, integrates concepts such as life cycle and extended producer responsibility into traditional supply chains. Relying on the supply relationships between upstream and downstream enterprises, with core

enterprises as pivots, it continuously promotes environmental performance improvement among chain enterprises through actions like green procurement, green supplier management, green logistics, and green recycling (Mao, 2022; Xie & Zhu, 2022; Li et al., 2025)[8][14][51]. Scholars generally define it as enterprises strategically and transparently coordinating the entire supply chain process, systematically integrating economic, environmental, and social goals, to foster interest symbiosis and value co-creation among various supply chain stakeholders, promoting long-term sustainability and resilience (Liu et al., 2025; Pagell & Wilhelm, 2025)[1][52]. This definition emphasizes that GSCM is not just about environmental compliance but also strategic synergy integrating the Triple Bottom Line of Economy, Society, and Environment (Han et al., 2024; Mohsin et al., 2025)[53][5].

International academia has extensively explored GSCM. Early research focused on improving environmental performance in single links like green procurement and green manufacturing, while current research emphasizes collaborative governance throughout the entire supply chain process and the synergistic optimization of economic, environmental, and social performance (Liu et al., 2025; Pagell & Wilhelm, 2025)[1][52]. At the driver level, scholars have revealed the motivations for firms to adopt GSCM from multiple dimensions, including coercive environmental regulatory pressure (Liu et al., 2025; Stendel et al., 2026)[7][13], market and stakeholder pressure (Tian et al., 2024; Li et al., 2025)[6][54], internal firm resources and capability bases (Liu et al., 2025; Xie & Zhu, 2022)[7][14], and peer effects and value network embeddedness (Xue et al., 2023)[10]. At the performance impact level, numerous empirical studies have confirmed that GSCM can significantly enhance corporate operational, environmental, and social performance (Xie & Zhu, 2022; Wang et al., 2024; Sharma et al., 2026; Opoku et al., 2025)[14][15][16][55]. Meta-analytical research further confirms that GSCM can significantly enhance green innovation and carbon-neutral supply chain performance, with strong sustainability infrastructure and regulatory environments amplifying this effect in high-income countries (Öztürk et al., 2026)[56]. At the transmission mechanism level, scholars have explored the internal mechanisms through which GSCM affects corporate performance via mediating pathways such as information sharing (Liu et al., 2025)[57], supply chain integration (Han et al., 2024)[53], green innovation (Gao & Zhu, 2025; Bu et al., 2025)[58][17], and knowledge management and absorptive capacity (Yin et al., 2025)[59]. Notably, corporate social responsibility (CSR) plays a significant mediating role between GSCM and sustainable performance (Alkandi, 2025)[60]. Furthermore, research on the spillover effects of GSCM is growing, confirming that GSCM can drive green innovation in upstream and downstream enterprises through supply chain transmission (Bu et al., 2025; Yan et al., 2024; Han et al., 2025; Quan & Zhou, 2025)[17][18][19][61], forming a diffusion effect of green innovation within the industrial chain (Li & Niu, 2025; Shi & Yan, 2024)[62][63]. At the industry level, scholars have conducted numerous contextual studies across different fields such as agriculture (Li, 2022; Ren et al., 2023; Bytyqi et al., 2026)[64][9][26], manufacturing (Tian et al., 2024; Jafaripour et al., 2026)[6][65], retail (Wang & Li, 2021; Yang, 2024)[66][67], and automotive (Tian et al., 2024; Sharma et al., 2026)[6][16], revealing the industry heterogeneity and practical characteristics of GSCM.

As a core driver of the new technological revolution, AI is profoundly reshaping corporate operational models and supply chain management logic (Shi et al., 2025; Yang & Liu, 2024)[20][21]. From an information processing perspective, with its powerful data perception, intelligent decision-making, and system optimization capabilities, AI can effectively integrate information flows across various supply chain nodes, significantly alleviating the prevalent issue of information asymmetry in traditional supply chains (Zhang, 2022; Meng & Hu, 2025; Zhang et al.,

2025)[22][23][24]. By optimizing supply-demand matching, improving logistics scheduling efficiency, and reducing transaction costs, AI significantly enhances overall supply chain efficiency (Zhang, 2022; Babaei et al., 2025; Aylak, 2025)[22][25][43], thereby establishing a solid operational foundation for GSCM. From a technological innovation perspective, AI can promote corporate green technology innovation, driving disruptive green innovation by enhancing the breadth and depth of knowledge search (Zhou et al., 2025; Chen et al., 2025)[27][28]. Its big data analytics capabilities enable firms to accurately identify green technology needs, reduce trial-and-error costs in green R&D, and accelerate the transformation of green technologies from labs to application scenarios (Yi & Yang, 2025)[68], thus deeply integrating environmental concepts into the entire supply chain process (Sharma et al., 2026; Thiyagarajan et al., 2026)[16][42]. From an ESG management perspective, AI applications help improve corporate ESG performance by enhancing the level of green technology innovation, increasing information transparency, and optimizing resource allocation (Xu et al., 2024; Tang et al., 2025; Lin & Huang, 2026)[29][30][31]. Its monitoring and early warning capabilities can precisely track carbon emissions throughout the supply chain, strengthening supplier compliance and social responsibility audits (Song et al., 2024; Guan & Zheng, 2026)[36][39]. From a supply chain resilience perspective, AI plays a role ranging from instrumental to strategic in shaping supply chain resilience, driving transitions through adaptive, continuous, and transformative resilience via human-machine collaboration (Song et al., 2024; Lyu et al., 2026; Zhang et al., 2026)[36][37][38]. AI-driven collaborative models can significantly improve supply chain coordination, predictive analytics, and automation processes, thereby enhancing operational efficiency and sustainability. In the circular supply chain domain, AI has become a key support for enterprises adopting circular economy practices, while in complex systems like healthcare supply chains, AI is evolving from an efficiency tool into a strategic enabler of decision intelligence, supporting real-time sensing, scenario analysis, and proactive risk mitigation (Paul et al., 2025; Sharma et al., 2026; Thiyagarajan et al., 2026)[41][16][42]. Based on the above analysis, this paper proposes the following hypothesis:

H1. AI application has a significant positive impact on green supply chain management.

2.2 The Mediating Role of Firm Internal Capabilities

The resource-based view and dynamic capabilities theory suggest that the source of a firm's sustainable competitive advantage lies in its unique resource endowment and capability building. In the context of green transformation, firm internal capabilities refer to the firm's capability for organizing, integrating, building, and reconfiguring internal and external resources to adapt to environmental changes and achieve sustainable development goals (Liu et al., 2025; Pagell & Wilhelm, 2025)[7][52]. As a general-purpose technology, AI's value creation is not automatic. Rather it requires activation and reshaping of firm internal capabilities as a key transmission mechanism (Shi et al., 2025)[20]. Based on this theoretical logic, this paper focuses on four core capability pathways through which AI enables GSCM: green innovation capability, ESG management capability, supply chain efficiency, and resource integration capability. Among these, green innovation reflects a firm's knowledge creation and application capability in driving green transformation at the technological level (Xie & Zhu, 2022)[14]; ESG performance embodies a firm's comprehensive management capability in environmental, social, and governance dimensions (Fang & Hu, 2023)[69]; supply chain efficiency demonstrates a firm's operational-level process optimization and resource allocation capability (Zhang, 2022)[22]; and resource integration represents a firm's capability to coordinate and allocate internal and external resources efficiently (He & Guo, 2026)[32]. These four capabilities are interconnected and mutually reinforcing, collectively forming the internal transmission chain through which AI enables GSCM. The

specific mechanisms for each pathway are elaborated below.

2.2.1. The Mediating Role of Green Innovation

Green innovation refers to new products, processes, or management models developed by enterprises to avoid or reduce the negative environmental impacts across various supply chain stages (Xie & Zhu, 2022)[14]. There is a close intrinsic link between AI and green innovation. From a knowledge acquisition perspective, with its powerful data processing and analysis capabilities, AI can efficiently mine green development needs, precisely match innovation resources, accelerate green technology R&D and implementation, and reduce the trial-and-error costs and R&D cycles of corporate green innovation (Zhou et al., 2025; Chen et al., 2025)[27][28]. From a knowledge reconfiguration perspective, AI can promote the expansion and restructuring of corporate knowledge bases, providing rich information for green innovation by enhancing the breadth and depth of search (Zhou et al., 2025; Yin et al., 2025)[27][59]. From a knowledge application perspective, AI's algorithmic optimization capabilities help make innovations in green technologies, processes, and operational models more targeted and effective, thereby effectively enhancing corporate green innovation capability (Xu et al., 2024; Tang et al., 2025)[29][30]. The application of AI in circular supply chains can significantly enhance the adoption of green innovation (Sharma et al., 2026; Abdallah-Ou-Moussa et al., 2026)[16][45], while AI-driven collaborative models provide new organizational vehicles for green innovation (Paul et al., 2025)[41].

Regarding the impact of green innovation on GSCM, green innovation is the core driver for implementing GSCM. First, green innovation can be transformed into specific green production technologies, green logistics solutions, and green control measures, optimizing the green operational efficiency of various supply chain links (Xie & Zhu, 2022; Gao & Zhu, 2025)[14][58]. Second, green innovation helps reduce environmental compliance costs in the supply chain and improve resource utilization efficiency, providing technical support for the implementation of various GSCM requirements (Bu et al., 2025; Öztürk et al., 2026)[17][56]. Finally, green innovation, through knowledge sharing and collaborative R&D, can drive upstream and downstream enterprises to jointly improve green management levels, generating significant supply chain spillover effects (Quan & Zhou, 2025; Li & Niu, 2025)[61][62]. Meta-analytical research further confirms that green innovation plays a key mediating role between GSCM and carbon-neutral performance (Öztürk et al., 2026)[56]. Based on the above analysis, this paper proposes the following hypothesis:

H2. Green innovation mediates the relationship between AI and green supply chain management.

2.2.2. The Mediating Role of ESG Performance

ESG performance, as a key indicator of corporate sustainable development capability, encompasses the environmental, social, and governance dimensions (Fang & Hu, 2023)[69]. The promoting effect of AI on ESG performance has been widely confirmed. From an environmental lens, AI can help enterprises effectively reduce carbon emissions and improve energy utilization efficiency through precise monitoring and intelligent analysis, thereby improving environmental performance (Xu et al., 2024; Tang et al., 2025)[29][30]. From a social lens, AI can optimize supply chain transparency and traceability, strengthen supplier social responsibility audits, and enhance social performance (Song et al., 2024; Guan & Zheng, 2026)[36][39]. From a governance lens, AI can enhance corporate information transparency and internal control levels, optimize corporate governance structures, and improve governance performance (Yang & Liu, 2024; Lin & Huang, 2026)[21][31]. AI-driven digital strategies can significantly enhance supply chain ESG performance, especially in industries with strict compliance requirements (Gastélum-Valdez et al., 2026; Alkandi, 2025)[70][60].

Regarding the impact of ESG performance on GSCM, good ESG performance provides operational assurance for companies to build efficient, transparent, and responsible GSCM systems. On the one hand, good environmental performance implies that enterprises possess solid foundational capabilities in green production, green procurement, and green logistics (Shi & Yan, 2024; Han et al., 2025)[63][19]. On the other hand, good social performance helps enterprises gain the trust and support of stakeholders, creating a favorable external environment for the collaborative advancement of GSCM (Yan et al., 2024; Guan & Zheng, 2025)[18][39]. Furthermore, ESG performance can drive green innovation in upstream and downstream enterprises through supply chain transmission (Yan et al., 2024; Han et al., 2025)[18][19], alleviate corporate financing constraints, provide financial support for GSCM (Wang et al., 2026)[71], and significantly enhance the resilience and sustainable performance of the supply chain (Fu, 2026)[72]. Based on the above analysis, this paper proposes the following hypothesis:

H3. ESG performance mediates the relationship between AI and green supply chain management.

2.2.3. The Mediating Role of Supply Chain Efficiency

Supply chain efficiency reflects the operational speed and resource allocation efficiency across various supply chain links and is an important indicator of supply chain management level (Zhang, 2022)[22]. The enhancing effect of AI on supply chain efficiency has been widely validated. From an operational optimization perspective, AI, through algorithmic optimization and intelligent decision-making, can drive the digital and intelligent upgrading of supply-demand matching, logistics scheduling, and production planning (Meng & Hu, 2025; Zhang et al., 2025)[23][24]. From an information processing perspective, AI can enhance supply chain visualization and traceability through real-time data collection and analysis, reducing information delays and operational errors (Song et al., 2024; Babaei et al., 2025)[36][25]. From a predictive decision-making perspective, AI-driven predictive analytics can accurately forecast market demand changes, optimizing inventory management and resource allocation (Zhang, 2022; Mouloudj et al., 2026)[22][44]. The synergistic application of technologies like digital twins and the Internet of Things with AI further amplifies the efficiency-enhancing effect (Thiyagarajan et al., 2026; Abdallah-Ou-Moussa et al., 2026)[42][45], while the agentic AI framework demonstrates how sustained learning can optimize procurement, logistics, and inventory decisions, achieving dual improvements in efficiency and sustainability (Aylak, 2025)[43].

Regarding the impact of supply chain efficiency on GSCM, improved supply chain efficiency provides a solid operational foundation for GSCM. First, efficient supply chains can reduce resource waste and inefficient behaviors, lowering energy consumption and carbon emissions (Zhang, 2022; Li et al., 2025)[22][73]. Second, efficient supply chain operations can accelerate the circulation and promotion of green technologies and products, facilitating the diffusion of green practices within the supply chain (Wang & Li, 2025)[74]. Finally, improved supply chain efficiency can significantly enhance a firm's environmental performance, creating favorable conditions for GSCM (Zhang et al., 2026)[75], while also helping reduce the costs of green transformation, alleviating the pressures enterprises face when advancing GSCM (Gu et al., 2024)[76]. Based on the above analysis, this paper proposes the following hypothesis:

H4. Supply chain efficiency mediates the relationship between AI and green supply chain management.

2.2.4. The Mediating Role of Resource Integration

Resource integration capability embodies a firm's ability to coordinate and allocate internal and

external resources, achieving optimal resource combinations. Total factor productivity (TFP) is a key indicator of resource integration efficiency (He & Guo, 2026; Jin et al., 2025)[32][33]. AI enhances resource integration capability in several ways. From a data integration perspective, AI possesses algorithmic capabilities for multi-source data integration and deep analysis, effectively integrating various resources within and outside the supply chain, such as human, material, financial, and information resources (Liu & Tan, 2026; Xu & Wang, 2025)[77][78]. From a resource allocation perspective, AI can achieve precise resource allocation and efficient utilization through intelligent matching and optimization scheduling (Qi & Cheng, 2025; Albulescu et al., 2025)[34][35]. From an efficiency improvement perspective, AI can effectively reduce resource misallocation and waste by enhancing information transparency and decision-making efficiency (He & Guo, 2026; Zhang et al., 2026)[32][75]. The synergistic application of AI and digital technologies can significantly improve TFP (Albulescu et al., 2025; Dutta et al., 2025)[35][79], while the agentic AI framework demonstrates how learning can optimize resource allocation, achieving both cost reduction and efficiency improvement (Aylak, 2025)[43].

Regarding the impact of resource integration on GSCM, resource integration capability is a crucial support for GSCM. On the one hand, resource integration capability can integrate the concept of green development into the entire process of resource matching and allocation, ensuring that resources for green production and green logistics are more reasonably distributed and utilized (Liu & Tan, 2026)[77]. On the other hand, resource integration can enhance the green utilization efficiency of the supply chain, reduce environmental governance costs, and strengthen a firm's ability to respond to environmental regulations (Li, 2025; Yang & Zhang, 2025)[80][81]. Furthermore, improvements in TFP can significantly promote corporate green innovation (Zhou & Zhu, 2025)[82] and enhance the green synergy capability of the supply chain (Gu et al., 2024)[76]. Firms with stronger resource integration capabilities are better able to transform external environmental pressures into internal drivers for green transformation, continuously improving GSCM levels (Xue et al., 2026)[83]. Based on the above analysis, this paper proposes the following hypothesis:

H5. Resource integration (total factor productivity) mediates the relationship between AI and green supply chain management.

Synthesizing the theoretical analysis above, AI empowers GSCM through four pathways: green innovation, ESG performance, supply chain efficiency, and resource integration, forming a chain transmission mechanism of "AI → firm internal capabilities → GSCM." Based on this, this study constructs the theoretical model, as shown in Figure 1.

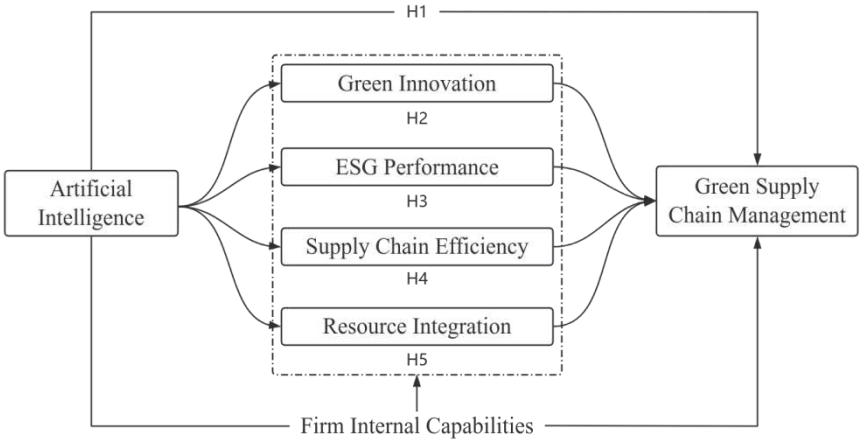

Figure 1. Theoretical Analysis Framework.

3. Research Design

3.1 Sample Selection and Data Sources

This paper selects Chinese A-share listed companies from 2016 to 2024 as the initial research sample. The sample period begins in 2016 mainly for two reasons: First, 2016 was a crucial year for the intensive issuance of GSCM policies. The Industrial Green Development Plan (2016–2020) and the Green Manufacturing Project Implementation Guide (2016–2020) released that year systematically proposed for the first time the construction of a green supply chain system, providing policy guidance for the practice and disclosure of GSCM. Second, 2016 also marked a significant watershed for the accelerated penetration of AI technology into corporate operations, with disclosures related to AI in annual reports beginning to increase significantly, providing a data foundation for identifying the level of corporate AI application.

The research data primarily comes from the CSMAR database, which covers comprehensive financial and governance information of Chinese listed companies and is widely used in relevant empirical research. To ensure data quality and the reliability of empirical results, this paper filters the initial sample as follows: (1) Excluding financial industry companies due to the special nature of their business models and financial structures; (2) Excluding companies with ST, *ST, or PT status during the year, as their abnormal operations may interfere with research conclusions; (3) Excluding samples with missing values for key variables. After the above processing, a final sample of 30,571 firm-year observations is obtained. To mitigate the potential impact of extreme values on regression results, all continuous variables are winsorized at the 1st and 99th percentiles.

3.2 Variable Measurement

3.2.1. Dependent Variable: Green Supply Chain Management (SSC)

Following the methodology of Bu et al. (2025)[17], this paper uses textual analysis to construct the corporate GSCM indicator. Specifically, based on the conceptual connotations of GSCM and policy document requirements, a keyword lexicon is constructed containing terms such as “green procurement,” “green supplier,” “green logistics,” “green recycling,” “life cycle management,” and “extended producer responsibility.” Python programs are used to identify and count keyword frequencies in the annual reports of listed companies. The natural logarithm of one plus the keyword frequency is used as the proxy variable for GSCM level. A larger value of this indicator indicates richer GSCM practices and more comprehensive disclosure by the company.

3.2.2. Independent Variable: Artificial Intelligence Application Level (NAI)

Drawing on the AI dictionary constructed by Yao et al. (2024)[84], this paper uses textual analysis to measure corporate AI application level. Based on the technical characteristics of AI and industrial application practices, a keyword lexicon is constructed containing core terms such as “machine learning,” “deep learning,” “neural network,” “natural language processing,” “computer vision,” and “intelligent algorithm.” Textual analysis is performed on the annual reports of listed companies to identify and count the occurrence frequency of AI-related keywords. The natural logarithm of one plus the frequency is used as the proxy variable for AI application level.

3.2.3. Control Variables

To mitigate omitted variable bias, drawing on the studies of Yao et al. (2024)[84] and Liu et al. (2025)[7], this paper selects the following variables that may affect corporate GSCM as control variables: firm size (Size), leverage ratio (Lev), fixed assets ratio (Fix), profitability (ROA), growth opportunity (Growth), CEO duality (Dual), firm age (ListAge), Tobin’s Q (Tobinq), shareholding ratio of the largest shareholder (TOP1), proportion of independent directors (Indep), board size (Board), and

ownership nature (SOE). The definitions of the main variables are shown in Table 1.

Table 1. Main Variable Definitions.

Variable Type	Variable Name	Symbol	Definition
Dependent Variable	Green Supply Chain Management	SSC	Ln (Annual report keyword frequency + 1)
Independent Variable	Artificial Intelligence	NAI	Ln (Annual report keyword frequency + 1)
Control Variables	Firm Size	Size	Natural logarithm of total assets
	Leverage Ratio	Lev	Total liabilities / Total assets at year-end
	Fixed Assets Ratio	Fix	Net fixed assets / Total assets at year-end
	Profitability	ROA	Net profit / Total assets at year-end
	Growth Opportunity	Growth	(Revenue_t - Revenue_{t-1}) / Revenue_{t-1}
	CEO Duality	Dual	Dummy variable, 1 if the Chairman and CEO are the same person, 0 otherwise
	Firm Age	ListAge	Natural logarithm of the number of years since listing
	Tobin's Q	Tobinq	Market value / Total assets
	Largest Shareholder	TOP1	Shareholding ratio of the largest shareholder
	Independent Director Ratio	Indep	Number of independent directors / Total board members
	Board Size	Board	Natural logarithm of the total number of board seats
	Ownership Nature	SOE	Dummy variable, 1 if the ultimate controller is state-owned, 0 otherwise

3.3 Model Specification

To test the impact of AI application on GSCM (Hypothesis H1), this paper constructs the two-way fixed effects baseline regression model:

$$SSC_{i,t} = \alpha_0 + \alpha_1 AI_{i,t} + \alpha_2 Controls_{i,t} + \sum Year + \sum Insudtry + \varepsilon_{i,t} \quad (1)$$

where i and t represent the firm and year, respectively. The dependent variable SSC denotes the GSCM level of firm i in year t. The core explanatory variable NAI denotes the AI application level of firm i in year t . According to Hypothesis 1, the coefficient is expected to be positive. εi,t is the random error term. Year and Ind represent firm and year fixed effects, respectively. Controls represent the set of control variables mentioned above.

4. Empirical Results Analysis

4.1 Descriptive Statistics

The descriptive statistics of the main variables are shown in Table 2. Regarding the dependent

variable, the mean value of GSCM (SSC) is 2.371, with a standard deviation of 0.833, a minimum of 0.693, and a maximum of 4.357, indicating significant differences in GSCM practice levels among sample firms, with some having established relatively mature GSCM systems while a considerable proportion are still in the early stages. Regarding the core explanatory variable, the mean value of AI application level (NAI) is 1.197, with a standard deviation of 1.310, a minimum of 0, and a maximum of 4.812, indicating that the degree of AI technology application among Chinese listed companies varies greatly; some firms have deeply integrated AI into their operations, while others have not yet engaged in related practices. This distribution provides a good data foundation for subsequent investigation of the impact of AI on GSCM. Regarding control variables, the mean firm size (Size) is 22.36, the mean leverage ratio (Lev) is 0.419, and the mean return on assets (ROA) is 0.028, with all variables falling within reasonable ranges, indicating a relatively stable sample distribution.

Table 2. Descriptive Statistics.

Variable	Obs	Mean	Std. Dev.	Min	Median	Max
SSC	30571	2.371	0.833	0.693	2.398	4.357
NAI	30571	1.197	1.310	0	0.693	4.812
Size	30571	22.36	1.283	20.09	22.16	26.380
Lev	30571	0.419	0.203	0.060	0.410	0.917
Fix	30571	0.200	0.149	0.002	0.170	0.656
ROA	30571	0.028	0.071	-0.301	0.033	0.194
Growth1	30571	0.129	0.356	-0.592	0.082	1.984
Dual	30571	0.324	0.468	0	0	1
ListAge	30571	3.053	0.289	2.197	3.091	3.664
Tobinq	30571	1.951	1.193	0.818	1.573	7.830
TOP1	30571	0.330	0.144	0.087	0.305	0.733
Indep	30571	0.379	0.0530	0.333	0.364	0.571
Board	30571	2.095	0.194	1.609	2.197	2.565
SOE	30571	0.297	0.457	0	0	1

4.2 Baseline Regression Analysis

The baseline regression results for the impact of AI application on GSCM are shown in Table 3. Column (1) presents a simple regression without any fixed effects or control variables, where the coefficient for AI (NAI) is 0.128, significantly positive at the 1% level. Column (2) includes industry and year fixed effects, and the coefficient for NAI is 0.076, still significant at the 1% level. Column (3) further includes control variables while controlling for both industry and year fixed effects; the coefficient for NAI is 0.101, and it remains significant at the 1% level. These results indicate that AI application has a significant positive effect on GSCM, providing preliminary support for Hypothesis H1. Regarding control variables, the coefficient for firm size (Size) is significantly positive at the 1% level, indicating that larger firms, with stronger resource integration and risk-bearing capabilities and more sophisticated management systems, are more conducive to promoting GSCM practices (Liu et al., 2025)[7]. The coefficient for profitability (ROA) is also significantly positive, suggesting that more profitable firms have greater capacity to invest in green supply chain initiatives. The coefficient for ownership nature (SOE) is significantly negative, indicating that state-owned enterprises have

relatively lower GSCM levels, possibly related to the multiple objective constraints they face.

Table 3. Baseline Regression Results.

Variable	(1)	(2)	(3)
	SSC	SSC	SSC
NAI	0.128***	0.076***	0.101***
	(14.91)	(10.39)	(12.44)
Size		0.161***	0.176***
		(15.72)	(19.90)
Lev		0.240***	0.259***
		(4.27)	(5.01)
Fix		0.740***	0.275***
		(10.67)	(3.87)
ROA		0.445***	0.224**
		(3.91)	(2.10)
Growth1		0.040***	0.096***
		(2.81)	(7.51)
Dual		0.074***	0.048***
		(3.97)	(2.87)
ListAge		0.033	-0.162***
		(0.99)	(-5.14)
Tobinq		-0.061***	-0.037***
		(-8.65)	(-5.54)
TOP1		-0.043	0.023
		(-0.64)	(0.37)
Indep		-0.581***	-0.398**
		(-2.88)	(-2.25)
Board		-0.194***	-0.037

		(-3.10)	(-0.68)
SOE		-0.196***	-0.107***
		(-7.77)	(-4.71)
Constant	2.170***	2.218***	-1.066***
	(161.71)	(164.60)	(-4.40)
Ind	Yes	No	Yes
Year	Yes	No	Yes
Observations	30,571	30,574	30,571
Adjusted R-squared	0.222	0.116	0.304

Note: *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively, the values of T are in parentheses, the following table is the same.

In economic terms, leveraging its powerful data analysis and intelligent decision-making capabilities, AI can effectively integrate information flows across supply chain links, mitigating information asymmetry (Zhang, 2022; Meng & Hu, 2025)[22][23]. Moreover, by optimizing supply-demand matching, logistics scheduling, and resource allocation efficiency, it reduces operational waste and inefficient behaviors, deeply integrating the concept of green development into supply chain planning, execution, and control, thereby enhancing GSCM levels. This finding aligns with the theoretical logic of Liu et al. (2025)[7] regarding how environmental regulations influence GSCM through internal capability transformation, also indirectly confirming the crucial role of technology-driven capabilities in green transformation.

4.3 Robustness Tests

4.3.1. Variable Substitution

To avoid the impact of variable measurement methods on the conclusions, this paper tests by substituting the explanatory and dependent variables separately. First, the natural logarithm of one plus the AI-related word frequency in the Management Discussion and Analysis (MD&A) section of the annual report is used as a substitute explanatory variable (MAI) for re-regression. The results in Column (1) of Table 4 show that the coefficient for MAI is 0.104, significant at the 1% level. Second, the natural logarithm of one plus the GSCM-related word frequency in the social responsibility report is used as a substitute dependent variable (SSC1) for regression. The results in Column (2) of Table 4 show that the coefficient for NAI is 0.084, significant at the 1% level. These results indicate that changes in variable measurement do not affect the robustness of the core conclusions.

Table 4. Robustness Test Results: Variable Substitution, Sample Period Change, and High-Dimensional FE.

Variable	**(1)**	**(2)**	**(3)**	**(4)**
	SSC	**SSC1**	**SSC**	**SSC**
MAI	0.104***			
	(12.74)			

NAI		0.084***	0.094***	0.083***
		(5.54)	(7.80)	(12.39)
Control	Yes	Yes	Yes	Yes
Ind	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Stkcd	No	No	No	Yes
Constant	-1.080***	-4.056***	-0.729**	-1.741***
	(-4.47)	(-9.44)	(-2.20)	(-2.96)
Observations	30,571	10,089	10,842	30,309
Adjusted R-squared	0.303	0.460	0.204	0.734

4.3.2. Sample Period Change and High-Dimensional Fixed Effects

Considering that the COVID-19 pandemic shock from 2020 onwards might have affected GSCM development through channels like policy controls and logistics restrictions, this paper excludes samples from 2020 onwards, retaining only the 2016-2019 sample for re-regression. The results in Column (3) of Table 4 show that the coefficient for NAI is 0.094, still significantly positive at the 1% level, indicating that the promoting effect of AI on GSCM is not driven by the special pandemic context. Furthermore, although the baseline regression already controls for industry and year fixed effects, to rule out heterogeneity at the firm level that does not vary over time, this paper further adds firm-specific fixed effects. The results in Column (4) of Table 4 show that the coefficient for NAI is 0.083, significant at the 1% level, and the conclusion remains robust.

4.3.3. Instrumental Variable Method

Although the baseline regression controls for multi-dimensional fixed effects, potential issues like reverse causality or omitted variables between AI application and GSCM might cause endogeneity bias. To mitigate this bias, this paper draws on the approach of Han et al. (2025)[85], using the average AI application level of other firms in the same province and year as an instrumental variable for two-stage least squares (2SLS) regression. This instrumental variable satisfies the relevance condition, as the overall AI technology application level in the firm's province influences its own application level. It also satisfies the exogeneity condition, as the AI application level of other firms in the same province does not directly affect the individual firm's GSCM. Table 5 reports the instrumental variable regression results. Column (1) shows the first-stage regression, where the coefficient for the instrumental variable (IV1) is 0.190, significant at the 1% level, and the Cragg-Donald Wald F statistic is 120.485, far exceeding the critical value at the 10% level, indicating no weak instrument problem. The Kleibergen-Paaprk LM statistic is 26.365 with a p-value of 0.000, rejecting the null hypothesis of under-identification. Column (2) shows the second-stage regression results, where the coefficient for NAI is 0.354, significant at the 5% level. The instrumental variable regression results further confirm the positive effect of AI on GSCM, suggesting that endogeneity does not pose a substantive threat to the core conclusions.

Table 5. Instrumental Variable Regression Results.

Variable	**(1)**	**(2)**
	first	**second**

IV1	0.190***	
	(5.12)	
NAI		0.354**
		(2.44)
Control	Yes	Yes
Ind	Yes	Yes
Year	Yes	Yes
Observations	30,569	30,569
CD Wald F	120.485	
KP rk LM	26.365	
	(0.000)	

4.3.4. Propensity Score Matching (PSM) Test

To mitigate estimation bias potentially caused by sample selection bias, this paper uses the Propensity Score Matching (PSM) method for robustness testing. First, a treatment group dummy variable is set based on whether the firm applies AI (taking 1 if NAI > 0, otherwise 0). The control variables from the baseline regression are used as covariates for 1:1 and 1:3 nearest neighbor matching. The kernel density plots after matching (Figures 2 and 3) show that the distribution characteristics of the treatment and control groups are significantly closer. After matching, there are no significant differences between the treatment and control groups for the covariates, indicating good matching results and satisfying the balancing assumption.

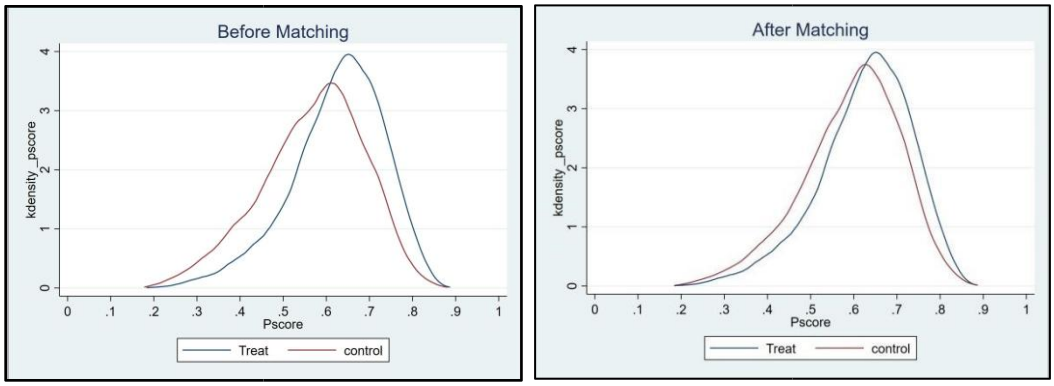

Figure 2. 1:1 Matching Kernel Density Plot.

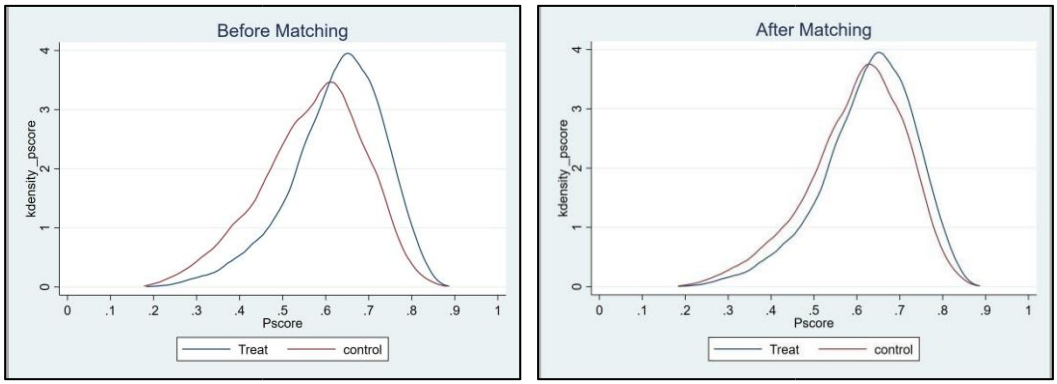

Figure 3. 1:3 Matching Kernel Density Plot.

Table 6 reports the regression results after PSM matching. Columns (1) and (3) are regressions without control variables, where the coefficients for NAI are 0.081 and 0.089, respectively, both significant at the 1% level. Columns (2) and (4) are regressions with control variables, where the coefficients for NAI are 0.067 and 0.077, respectively, also significant at the 1% level. These results indicate that after controlling for sample selection bias, the promoting effect of AI on GSCM remains robust.

Table 6. PSM Regression Results.

Variable	1:1 Matching		1:3 Matching	
	SSC	SSC	SSC	SSC
NAI	0.081***	0.067***	0.089***	0.077***
	(5.58)	(4.70)	(9.57)	(7.81)
Control	NO	Yes	NO	Yes
Ind	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	14,241	14,241	24,926	24,926
Adjusted R-squared	0.724	0.733	0.723	0.732

4.4 Mechanism Testing

The baseline regression results have confirmed that AI has a significant positive impact on GSCM. This section further tests the transmission mechanism, i.e., whether AI indirectly promotes GSCM by enhancing firm internal capabilities (green innovation, ESG performance, supply chain efficiency, resource integration). Drawing on the mediation effect testing method of Wen and Ye (2014)[86], this paper constructs the following stepwise regression model:

$$M_{i,t} = \alpha_0 + \alpha_1 NAI_{i,t} + \alpha_2 Controls_{i,t} + \sum Year + \sum Insudtry + \varepsilon_{i,t} (2)$$

$$SSC_{i,t} = \alpha_0 + \alpha_1 NAI_{i,t} + \alpha_2 Controls_{i,t} + \alpha_3 M_{i,t} + \sum Year + \sum Insudtry + \varepsilon_{i,t} (3)$$

where Mi,t represents the mechanism variables. The control variables are the same as in model (1), and industry and year fixed effects are also controlled.

4.4.1. The Mediating Role of Green Innovation

Leveraging its powerful data processing and analysis capabilities, AI can efficiently mine green development needs, precisely match innovation resources, accelerate green technology R&D and implementation (Zhou et al., 2025; Chen et al., 2025)[27][28], thereby effectively enhancing corporate green innovation capability. As the core driver for implementing GSCM, green innovation can be transformed into specific green production technologies, green logistics solutions, and green control measures, optimizing the green operational efficiency of various supply chain links (Xie & Zhu, 2022; Gao & Zhu, 2025)[14][58]. This paper draws on Wang et al. (2023)[87], using the natural logarithm of one plus the number of green patents to measure green innovation. The results in Column (1) of Table 7 show that the coefficient of NAI on green innovation is 0.069, significantly positive at the 1% level, indicating that AI significantly promotes corporate green innovation. After including green innovation in the model in Column (2), the coefficient for green innovation is 0.025, significantly positive at the 1%

level, while the coefficient for NAI decreases from 0.101 in the baseline regression to 0.099. The Bootstrap test confirms that the mediating effect of green innovation is significant within the 95% confidence interval, with the mediating effect accounting for approximately 3.2%. These results validate the partial mediating role of green innovation between AI and GSCM, supporting Hypothesis H2.

Table 7. Mediation Test Results: Green Innovation and ESG Performance.

Variable	(1)	(2)	(3)	(4)
	Green	**SSC**	**ESG**	**SSC**
NAI	0.069***	0.099***	0.070***	0.098***
	(7.47)	(12.19)	(7.44)	(12.08)
Green		0.025***		
		(2.61)		
ESG				039***
				(7.07)
Control	Yes	Yes	Yes	Yes
Ind	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	20,786	20,786	30,568	30,568
Adjusted R-squared	0.159	0.279	0.400	0.305
Boostarp(5000)	[0.0052，0.0077]		[0.0026，0.0047]	

4.4.2. The Mediating Role of ESG Performance

AI can help enterprises effectively reduce carbon emissions and improve energy efficiency through precise monitoring and intelligent analysis (Xu et al., 2024; Tang et al., 2025)[29][30], optimize supply chain transparency and traceability (Song et al., 2024)[36], and enhance information transparency and internal control levels (Yang & Liu, 2024)[21], thereby improving corporate ESG performance. Good ESG performance provides operational assurance for companies to build efficient, transparent, and responsible GSCM systems (Shi & Yan, 2024; Han et al., 2025)[63][19]. This paper draws on Fang and Hu (2023)[69], using the Huazheng ESG rating as a proxy for ESG performance. The results in Column (3) of Table 7 show that the coefficient of NAI on ESG performance is 0.070, significant at the 1% level. After including ESG performance in the model in Column (4), the coefficient for ESG performance is 0.039, significant at the 1% level, while the coefficient for NAI decreases from 0.101 to 0.098. The Bootstrap test confirms the significance of the mediating effect of ESG performance, with the mediating effect accounting for approximately 4.0%. Thus, Hypothesis H3 is supported.

4.4.3. The Mediating Role of Supply Chain Efficiency

AI drives the digital and intelligent upgrading of supply-demand matching, logistics scheduling, and production planning through algorithmic optimization and intelligent decision-making (Meng & Hu, 2025; Zhang et al., 2025)[23][24], significantly improving the operational efficiency of various supply chain links. Efficient supply chains can reduce resource waste and inefficient behaviors,

lowering energy consumption and carbon emissions (Zhang, 2022; Li et al., 2025)[22][73], providing a solid operational foundation for GSCM. This paper draws on Zhang et al. (2023)[88], using ln(365 / total asset turnover) to measure supply chain efficiency. The results in Column (1) of Table 8 show that the coefficient of NAI on Turnover is -0.031, significant at the 1% level, indicating that AI significantly improves supply chain efficiency. After including supply chain efficiency in the model in Column (2), the coefficient for Turnover is -0.062, significant at the 1% level, indicating that improved supply chain efficiency positively promotes GSCM. Meanwhile, the coefficient for NAI decreases from 0.101 to 0.099. The Bootstrap test confirms the significance of the mediating effect, supporting Hypothesis H4.

Table 8. Mediation Test Results: Supply Chain Efficiency and Resource Integration.

Variable	(1)	(2)	(3)	(4)
	Turnover	**SSC**	**TFP_LP**	**SSC**
NAI	-0.031***	0.099***	0.021***	0.099***
	(-5.04)	(12.20)	(3.62)	(12.14)
Turnover		-0.062***		
		(-3.90)		
TFP_LP				0.050***
				(2.85)
Control	Yes	Yes	Yes	Yes
Ind	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	30,568	30,568	29,951	29,951
Adjusted R-squared	0.400	0.305	0.787	0.304
Boostarp(5000)	[0.0028，0.0046]		[0.0007，0.002]	

4.4.4. The Mediating Role of Resource Integration

AI possesses algorithmic capabilities for multi-source data integration and deep analysis, effectively integrating various resources within and outside the supply chain (Liu & Tan, 2026)[77], achieving precise resource allocation and efficient utilization through intelligent matching and optimization scheduling (Qi & Cheng, 2025)[34]. Resource integration capability can integrate the concept of green development into the entire process of resource matching and allocation, ensuring that resources for green production and green logistics are more reasonably distributed and utilized (Liu & Tan, 2026)[77]. This paper draws on Su (2026)[89], using total factor productivity (calculated using the LP method) to measure corporate resource integration level. The results in Column (3) of Table 8 show that the coefficient of NAI on TFP_LP is 0.021, significant at the 1% level, indicating that AI significantly improves TFP. After including TFP in the model in Column (4), the coefficient for TFP_LP is 0.050, significant at the 1% level, while the coefficient for NAI decreases from 0.101 to 0.099. The Bootstrap test confirms the significance of the mediating effect of resource integration, supporting Hypothesis H5.

Synthesizing the mechanism test results above, AI indirectly promotes GSCM by enhancing four pathways: green innovation, ESG performance, supply chain efficiency, and resource integration. These

four pathways collectively constitute the chain transmission mechanism of "AI → firm internal capabilities → GSCM," validating the theoretical analysis framework of this study.

5. Further Analysis

The preceding empirical results have confirmed that AI has a significant positive effect on GSCM, and this effect is realized through the four pathways of enhancing green innovation, ESG performance, supply chain efficiency, and resource integration. However, the enabling effect of AI may be influenced by internal and external contextual factors. Firms with different ownership natures, environmental information disclosure quality, and industry pollution attributes exhibit significant differences in resource allocation, information transparency, and environmental pressure, which may lead to heterogeneity in the effect of AI. Therefore, this section examines the boundary conditions of AI's impact on GSCM from three dimensions: firm ownership, information disclosure quality, and industry characteristics.

5.1 The Moderating Role of Ownership Nature

From the perspective of firm ownership, state-owned enterprises (SOEs) have unique advantages in resource endowment, information environment, and social responsibility assumption. SOEs have higher norms for information disclosure and more robust institutional systems, providing a more solid data foundation and institutional guarantee for AI application (Liu et al., 2025)[90]. Additionally, as key executors of national strategies, SOEs bear clearer political responsibilities and social expectations regarding green transformation, making their adoption and application of AI technology more likely to receive internal resource support and external policy incentives. Therefore, the optimization effect of AI on the information environment can play a greater role in SOEs based on a more solid information base, thereby more effectively alleviating supply chain information asymmetry and promoting GSCM practices.

To test the moderating role of ownership nature, this paper draws on the method of Zhai et al. (2022)[91], constructing an interaction term between AI and ownership nature (NAI×SOE). The results are shown in Column (1) of Table 9. The coefficient for AI (NAI) is 0.092, significantly positive at the 1% level; the coefficient for the interaction term (NAI×SOE) is 0.036, significantly positive at the 5% level. This indicates that compared to non-state-owned enterprises, the promoting effect of AI on GSCM is more significant in SOEs. This finding aligns with expectations and confirms that SOEs, leveraging their institutional advantages and information base, can better transform AI technology into a driver for green transformation (Liu & Tan, 2026)[77].

Table 9. Heterogeneity Analysis Regression Results.

Variable	(1)	(2)	(3)
	SSC	SSC	SSC
NAI	0.092***	0.091***	0.091***
	(10.52)	(9.51)	(10.70)
NAI*SOE	0.036**		
	(2.48)		
SOE	-0.144***		

	(-5.28)		
NAI*EQI		0.020*	
		(1.91)	
EQI		0.174***	
		(8.98)	
NAI*HAT			0.089***
			(3.72)
HAT			0.128*
			(1.92)
Control	Yes	Yes	Yes
Stkcd	Yes	Yes	Yes
Year	Yes	Yes	Yes
Observations	30,571	30,534	30,565
Adjusted R-squared	0.304	0.314	0.305

5.2 The Moderating Role of Environmental Information Disclosure Quality

High environmental information disclosure quality significantly amplifies the effect of AI. From an information base perspective, high disclosure quality itself implies higher corporate information transparency and more solid data foundations, providing more accurate base data for AI's big data analysis, risk prediction, and full-process monitoring, thus further enhancing AI's efficiency in optimizing the supply chain information environment (Zhang et al., 2026)[75]. From a stakeholder interaction perspective, the higher the environmental information disclosure quality, the clearer the supply chain partners' understanding of the firm's operating conditions and green compliance. This makes it easier to gain partners' cooperation and support during AI-driven supply chain efficiency improvements and resource optimization, thereby improving the effectiveness of technology implementation.

To test the moderating role of environmental information disclosure quality, this paper draws on the method of Kong et al. (2021)[92], setting a dummy variable for environmental information disclosure quality (EQI). Specifically, based on the corporate environmental information disclosure score, firms are grouped by the sample median; those above the median are assigned a value of 1, otherwise 0. The regression results are shown in Column (2) of Table 9. The coefficient for AI (NAI) is 0.091, significant at the 1% level; the coefficient for the interaction term (NAI×EQI) is 0.020, significant at the 10% level. The results indicate that when corporate environmental information disclosure quality is higher, the promoting effect of AI on GSCM is more significant. This finding echoes the conclusions of Shi and Yan (2024)[63] and Han et al. (2025)[19], confirming the crucial role of the information environment in the technology-enabled green transformation process.

5.3 The Moderating Role of Industry Pollution Attributes

From the industry attribute perspective, heavily polluting industries have a higher dependence on upstream and downstream resources and capacity. Their production operations and environmental governance processes are more complex, and information asymmetry is more pronounced (Wang et al.,

2025)[93]. AI's optimization effect on the information environment can more efficiently integrate multi-source data, alleviate information barriers among supply chain nodes, and enhance risk early warning and response capabilities. Simultaneously, heavily polluting industries face stricter environmental regulatory pressures (Pan et al., 2019)[94], giving firms more incentive to leverage AI technology to improve supply chain efficiency and environmental performance. Therefore, compared with non-heavily polluting industries, the promoting effect of AI on GSCM should be more pronounced in heavily polluting industries.

To test the moderating role of industry pollution attributes, this paper draws on the study of Pan et al. (2019)[94], setting a dummy variable for heavily polluting industries (HAT), assigned 1 if the firm belongs to a heavily polluting industry, otherwise 0. The regression results are shown in Column (3) of Table 9. The coefficient for AI (NAI) is 0.091, significant at the 1% level, and the coefficient for the interaction term (NAI×HAT) is 0.089, significant at the 1% level. The results indicate that when a firm belongs to a heavily polluting industry, the promoting effect of AI on GSCM is significantly enhanced. This finding suggests that in industries facing greater environmental pressure and more urgent green transformation needs, the enabling effect of AI technology can be more fully realized (Tian et al., 2024; Sharma et al., 2026)[6][16].

6. Research Conclusions, Policy Recommendations, and Limitations

6.1 Research Conclusions

Based on the resource-based view and dynamic capabilities theory, this paper constructs an integrated theoretical framework of "AI → firm internal capabilities → GSCM." Using a sample of Chinese A-share listed companies from 2016 to 2024, it employs various econometric methods, including two-way fixed effects models, instrumental variable methods, and propensity score matching, to systematically investigate the impact, transmission mechanisms, and heterogeneity of AI on GSCM. The findings are as follows: First, AI application has a significant positive effect on GSCM. Second, mechanism tests show that AI indirectly promotes GSCM by enhancing firm internal capabilities, specifically through four mediating pathways: green innovation, ESG performance, supply chain efficiency, and resource integration. Third, heterogeneity analysis reveals that the promoting effect of AI on GSCM is more pronounced in state-owned enterprises, firms with higher environmental information disclosure quality, and firms in heavily polluting industries.

6.2 Policy Recommendations

First, strengthen the deep integration of AI and GSCM to build a new technology-driven paradigm for green transformation. The government should increase policy support for AI applications in the supply chain domain, establish special guiding funds, and support enterprises in integrating AI with supply chain management for innovative development. Concurrently, it should accelerate the development of standard systems and evaluation frameworks for AI-enabled green supply chains, providing guidance for enterprises on technology application and effect assessment. Tax incentives and green credit policies could be offered to enterprises that excel in AI-enabled GSCM, creating a positive guidance mechanism.

Second, improve the cultivation mechanism for firm internal capabilities to smooth the transmission pathways for AI-enabled green transformation. This paper finds that AI's promoting effect on GSCM is mainly achieved through four pathways: enhancing green innovation, ESG performance, supply chain efficiency, and resource integration. Therefore, policy formulation should focus on unblocking these key transmission links. Specifically: (1) Improve the support system for green

technology innovation, establishing special funds for green technology R&D and encouraging enterprises to combine AI with green technologies; (2) Strengthen the construction of ESG information disclosure systems, promoting the standardization and comparability of ESG information to provide a data foundation for AI-enabled ESG management; (3) Guide enterprises to use AI to optimize supply chain processes and improve resource utilization efficiency; (4) Support enterprises in integrating internal and external resources, enhancing total factor productivity to establish an operational foundation for GSCM.

Third, implement a precision guidance mechanism based on categorization to leverage the synergistic enabling effects of diverse actors. The study finds that the promoting effect of AI on GSCM is more significant in state-owned enterprises, firms with higher environmental information disclosure quality, and firms in heavily polluting industries. This suggests that policy formulation should adopt differentiated guidance based on the characteristics of different subjects. First, leverage the exemplary and leading role of state-owned enterprises in green transformation, incorporating their AI and GSCM practices into performance evaluation systems, establishing benchmark demonstration projects, and forming replicable models. Simultaneously, provide policy guidance and technical support to help non-state-owned enterprises address their deficiencies in information base and resource guarantees. Second, optimize the information disclosure regulatory framework, improve the environmental information disclosure system, promote the standardization and comparability of information, strengthen third-party verification, and provide a solid data foundation for AI enablement. Third, focus on the green transformation needs of heavily polluting industries, formulate special policies to support enterprises in using AI to optimize production processes and reduce emissions, establish special funds for green transformation, and guide leading enterprises to drive upstream and downstream collaboration in promoting AI applications and green supply chain construction.

6.3 Limitations

Although this paper has conducted a relatively systematic study in theoretical analysis and empirical testing, it still has the following two limitations that need further research: First, the limitation of the research sample. This paper uses Chinese A-share listed companies as the research sample. While A-share listed companies cover major enterprises across various industries in China and have good representativeness, whether the conclusions apply to non-listed companies, small and medium-sized enterprises, and enterprises in different institutional contexts in other countries requires further testing. Future research could expand the sample scope to examine the differences and applicability of AI-enabled GSCM across different types of enterprises. Second, the limitation of external contextual factors. This paper examines heterogeneity from three perspectives: ownership nature, environmental information disclosure quality, and industry pollution attributes. However, the external environment in which enterprises operate (such as marketization degree, environmental regulation intensity, regional digital infrastructure level) may also affect AI's enabling effect. Future research could incorporate more macro and meso-level contextual factors, construct a cross-level theoretical analysis framework, and more comprehensively reveal the boundary conditions of AI-enabled GSCM.

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Data Availability Statement

Data is available on request to the authors.

Competing Interest Declaration

There are no conflicts of interest to declare in the submission of this manuscript, and all authors have read and approved the manuscript and agree to its submission to your esteemed journal.

Ethical Statement

This study did not involve human or animal subjects, and thus, no ethical approval was required. The study protocol adhered to the guidelines established by the journal.

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Author Contribution Declaration

Enlu Jiang contributed to the writing of Sections 5 (Further Analysis) and 6 (Research Conclusions, Policy Recommendations, and Limitations), and participated in data interpretation and visualization. Qian Cheng contributed to the writing of Sections 3 (Research Design) and 4 (Empirical Results Analysis), and performed the formal analysis and methodology development. Haoqing Jiang

conceived the conceptual framework, wrote the Abstract, Introduction, and Section 2 (Theoretical Analysis and Research Hypotheses), and prepared Figure 1. All authors reviewed, edited, and approved the final manuscript.

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