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The Impact of Artificial Intelligence on Corporate Green Value Co-Creation——Empirical Evidence from China's Manufacturing Industry

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Abstract

Against the dual demands of green transformation and digital integration in the manufacturing industry, green value co-creation has become a core pathway for enterprises to integrate stakeholder resources and synergize ecological and economic values, with the widespread application of artificial intelligence (AI) providing critical enabling support. Drawing on panel data of Chinese A-share listed manufacturing firms on the Shanghai and Shenzhen Stock Exchanges from 2015 to 2024, this study investigates the impact of AI development on corporate green value co-creation and its intrinsic mechanism. The results demonstrate that: AI development exerts a significantly positive effect on manufacturing enterprises' green value co-creation, which is achieved by enhancing firms' technological spillover capacity and total factor productivity (TFP); financing constraints negatively moderate the aforementioned relationship, while corporate influence plays a positive moderating role; heterogeneity analysis reveals that this impact is more pronounced for enterprises under voluntary regulation, state-owned enterprises (SOEs), and high-pollution enterprises. This study elucidates AI's role and mechanism in corporate green development at the micro level, provides empirical evidence for related research, and offers practical insights to promote enterprise AI advancement and green value co-creation.

Keywords: artificial intelligence; green value co-creation; green technological innovation; machine learning

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1. Introduction

With the intensification of global warming, frequent extreme weather events, and the growing prominence of environmental issues such as ecosystem degradation, green governance has become a global consensus. The United Nations explicitly defined the Sustainable Development Goals (SDGs) through the 2030 Agenda for Sustainable Development, advocating that countries promote green transformation with a multilateral cooperation stance [1]. As the world's largest developing country and a responsible major power, the Chinese government actively responds to international calls, integrates green governance and green development into the national strategy for high-quality development, and advances green economic transformation via policy guidance, technological innovation, and market mechanism reforms [2]. Despite remarkable progress in global sustainable development in recent years, challenges remain—including imperfect coordination mechanisms, insufficient technology transfer efficiency, and unbalanced regional development—urging the exploration of systematic solutions [3]. As a core pillar of the national economy, the manufacturing industry is not only a critical carrier of technological innovation but also a major contributor to energy consumption and carbon emissions. Its green development is directly linked to the advancement of China's "dual carbon" goals and the quality of participation in global environmental governance [4].

For manufacturing enterprises, green development faces technical hurdles such as substantial capital requirements and long cycles for achievement transformation [5], as well as management dilemmas including difficulties in managers' ideological transition and misalignment between corporate strategies and green development. Derived from sustainable development theory, the green value co-creation theory breaks the traditional one-way value chain and emphasizes multi-stakeholder collaboration to synergize environmental, economic, and social values [6]. By sharing resources and conducting collaborative innovation with stakeholders—including upstream and downstream enterprises, industry peers, and research institutions—manufacturing enterprises can collectively enhance green innovation capability, improve green technology transfer efficiency, and achieve multi-agent green value co-creation. Currently, academia recognizes green value co-creation as a key link for enterprises to integrate internal green resources and realize green innovation [7], a core bridge to enhance performance [8], and a critical pathway to meet green and sustainable development demands and build a dynamic value chain [9].

Artificial Intelligence (AI) is a comprehensive digital technology relying on algorithm models, data resources, and computing power, which simulates human cognitive logic and decision-making processes, automates task execution, and optimizes the resolution of complex problems [10]. As a core technological engine, AI reshapes social production methods, drives corporate innovation, and addresses environmental challenges [11]. From a societal perspective, AI facilitates the green upgrading of urban governance [12] and public services through technologies such as intelligent monitoring [13] and resource scheduling optimization. For enterprises, AI eliminates the experience dependence of traditional production, enabling cost reduction and efficiency improvement in scenarios like predictive maintenance and process optimization [14]. In green development, AI has become a key tool to achieve carbon emission reduction targets [15]. According to calculations by the China Academy of Information and Communications Technology, full application of AI-enabled green manufacturing technologies in core industries can reduce cumulative carbon emissions by over 2 billion tons, demonstrating its significant environmental value potential. Essentially, AI empowers enterprises to establish stakeholder resource-sharing platforms, break traditional information barriers, and promote resource sharing, collaborative innovation, and value co-creation. Additionally, AI enables real time monitoring of internal operational data, collection of external environmental data, and integrated analysis providing technical support for corporate green value co-creation. However, existing research on AI's impact on green development primarily focuses on the green economic effects of industrial intelligence in developing countries [16], the mediating role of knowledge coupling in AI-driven corporate green technological innovation [17], and AI's influence on sustainable development performance [18]. Scholarly exploration of AI's role and underlying mechanisms in corporate green value co-creation remains relatively scarce.

This study makes the following marginal contributions: First, while existing research mostly adopts a theoretical perspective to analyze AI's impact on green value co-creation, empirical evidence is limited. Using micro-level panel data of Chinese A-share listed manufacturing firms on the Shanghai and Shenzhen Stock Exchanges, this study conducts empirical validation to unveil the impact of AI development on manufacturing enterprises' green value co-creation, filling the empirical gap in this field. Second, beyond exploring the direct relationship between AI and green value co-creation, this study introduces two mediating variables—technological spillover and total factor productivity (TFP)—to clarify the transmission mechanisms through which AI exerts its effects. Third, this study investigates the moderating roles of financing constraints and corporate influence, identifying the contextual conditions that amplify or weaken AI's impact on green value co-creation. Fourth, integrating institutional contexts, this study performs heterogeneity analysis to explore inter-group differences in the aforementioned relationship, providing empirical support for different types of enterprises to formulate targeted and differentiated green development strategies.

2. Theoretical Analysis and Research Hypotheses

2.1. The Impact of Artificial Intelligence (AI) on Corporate Green Value Co-Creation

The value co-creation theory was first proposed by C.K. Prahalad and Venkatram Ramaswamy, and later further expanded through perspectives such as the service-dominant logic by Vargo and Lusch. Its core is to break the traditional cognition that enterprises unilaterally create value while consumers passively accept it, advocating that value is not solely determined and created by enterprises but jointly constructed through interactive collaboration among multiple stakeholders including enterprises, consumers, suppliers, and partners. This study is conducted based on the value co-creation theory, which abandons the traditional logic of enterprises creating value and customers passively receiving it, and advocates that enterprises and diverse stakeholders such as customers jointly participate in the entire process of value creation through interactive collaboration [19].

With the development of AI, traditional value co-creation centered on "resource integration" has gradually shifted to "intelligent collaboration." AI is an interdisciplinary frontier field integrating computer science, mathematics, neuroscience, and other disciplines. Its core aim is to simulate, extend, and expand human intelligent behaviors and cognitive abilities through algorithm design, model construction, and system implementation. Based on data, and with the support of key technologies such as machine learning, deep learning, natural language processing, and computer vision, AI enables machines to perceive the environment, understand information, conduct reasoning and decision-making, engage in autonomous learning, and achieve adaptive optimization. Ultimately, it facilitates the construction of intelligent systems capable of completing complex tasks without direct human intervention. The application of AI technology enables value matching among enterprise stakeholders to break free from time and space constraints. Enterprises can achieve real-time connection with scientific research institutions, suppliers, and distributors regarding green technology needs, converting scattered green resources into a synergistic force for co-creation. The impact of AI on green value co-creation of manufacturing enterprises is reflected in: First, breaking the barriers to technological co-creation [20]. Promoting the cross-domain flow of green knowledge is one of the core values of AI. In terms of cross-domain integration, AI can integrate green practical experiences from different enterprises and industries, establish a green knowledge base covering multiple industries, fields, and dimensions. It helps enterprises broaden their horizons, break free from information cocoons, transcend the limitations of a single industry, and jointly develop more innovative green technologies with stakeholders. Second, reducing multi-agent transaction costs [21]. High inter-agent collaboration costs have long been a key challenge in the process of corporate green value co-creation. AI can significantly reduce this cost by restructuring collaboration processes. From the perspective of the supply chain, AI can optimize procurement processes, production plans, and logistics routes, enabling enterprises to form linkages with suppliers and distributors and avoid resource waste caused by information lag. From the perspective of information disclosure, AI can automatically integrate green data and generate reports, reducing the labor costs of corporate information disclosure. Meanwhile, it ensures the efficient circulation of information among entities participating in green value co-creation, and guarantees that the outcomes of green value co-creation meet the standards and requirements of multiple parties. This reduces the opportunity costs incurred by enterprises in routine administrative work, allowing them to focus more efforts on green value co-creation. Third, constructing a full life cycle co-creation system [22]. AI extends green value co-creation from end-of-pipe emission reduction to full life cycle management and control. Existing green value co-creation mainly focuses on end-point greening—measures to reduce pollutant emissions through green technologies, green management, or behavioral means at the sales stage of resources. However, with the large-scale deployment of AI in enterprises' production and management, it can real-time monitor the full-process carbon footprint including production, transportation, and usage, and issue timely warnings when exceeding standards, ensuring that the green value co-creation process always adheres to low-carbon and green goals. Therefore, this study proposes the following hypothesis:

H1: Artificial intelligence can promote green value co-creation of manufacturing enterprises.

2.2. Mechanisms Underlying the Impact of Artificial Intelligence on Green Value Co-Creation in Manufacturing Enterprises

2.2.1. The Mediating Role of Technological Spillover

Technological spillover refers to the knowledge spillover effect formed by enterprises through technological R&D and application, and its intensity and scope determine the depth of synergy in green value co-creation [23]. Traditional technological spillover is often difficult for peers to effectively absorb due to its complexity and professional barriers, and this issue is more prominent in the field of green technology. As green technology involves an interdisciplinary knowledge system including energy management optimization and material recycling, and plays a crucial role in enterprise cost control, the phenomenon of patent "black boxes" frequently occurs in traditional technological spillover related to green technology.

However, in the context of AI empowerment, owing to its prominent capabilities in processing unstructured data, reverse-inferring algorithmic logic, and natural language processing [24]. On the one hand, it can realize the structured and semantic analysis of patent texts, accurately identifying the technological features with ambiguous expressions in "black-box" patents. On the other hand, through machine learning models, AI performs simulation and identification on a large volume of operation logs, process data, and environmental indicators. This significantly lowers the threshold for knowledge acquisition in the specific application of green production technologies, externalizing the tacit knowledge that previously required a large number of senior data science talents to access. Therefore, AI can effectively break the "black-box" phenomenon related to green technologies.

In addition, technological spillover is transmitted through multiple channels, directly exerting a systematic enabling effect on corporate green value co-creation, with its impact paths showing distinct characteristics of directness and pervasiveness. Vertical spillover in the supply chain, through the direct transfer of green production technologies between upstream and downstream enterprises, promotes the formation of a green technology collaborative adaptation system across all links of the industrial chain, realizing the connection of co-created value across the production, circulation, and consumption stages; Horizontal industrial spillover, by virtue of the green technology demonstration effect of leading enterprises in the same industry, reduces redundant investment in green technology R&D among enterprises and accelerates the formation of consensus on green technology standards within the industry. It provides a unified technical foundation for multiple subjects to carry out large-scale green value co-creation. AI promotes real-time technological interaction and collaborative innovation among co-creation subjects, ultimately driving the evolution of corporate green value co-creation from decentralized technological cooperation to an ecological model featuring industrial chain collaboration and multi-agent interest symbiosis, thereby realizing the synergistic value-added of green technology value and market value.

H2: Artificial intelligence can enhance the technological spillover capacity of manufacturing enterprises, thereby promoting their green value co-creation.

2.2.2. The Mediating Role of Production Efficiency

Total Factor Productivity (TFP), as the core indicator for measuring the comprehensive efficiency of converting factor inputs into outputs, is enhanced through technological progress, efficiency optimization, and innovation-driven growth. AI improves the TFP of manufacturing enterprises by advancing technical efficiency, allocative efficiency, and dynamic innovation efficiency. Firstly, AI can reduce inefficient inputs in enterprises' green production. Based on machine learning algorithms, AI optimizes production processes in real time, enhances the conversion rate of production factors such as energy and materials, and mitigates excessive energy consumption caused by irrational production procedures. Secondly, AI enables the optimal green allocation of production factors. It helps break information asymmetry, promotes the tilt of labor, capital, energy, and other factors toward green production links, and improves allocative efficiency. Through algorithmic analysis and platform integration, AI guides enterprises to transform production and procurement links toward

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low-carbonization and prioritize capital allocation to green technologies. Finally, AI accelerates the R&D and transformation cycle of green technologies. By reducing the R&D costs of green technological innovation and shortening the iteration cycle, AI boosts dynamic innovation efficiency, providing sustained technological impetus for productivity growth.

The optimization of production efficiency is not confined to cost reduction and efficiency improvement, but also provides material and capacity support for green value co-creation through the resource reallocation effect. Firstly, the reduction in unit costs brought about by efficiency improvement releases additional financial resources, which enterprises can invest in green technology R&D, the construction of co-creation platforms, or green cooperation projects, addressing the common challenge of insufficient resource input in green co-creation. Secondly, the data-driven capabilities formed in the process of production efficiency improvement can be transformed into collaborative capabilities in co-creation, reducing the communication costs and coordination difficulties of cross-agent cooperation, and promoting the upgrading of green value co-creation from fragmented cooperation to systematic collaboration.

The improvement of production efficiency not only acts on the enterprises themselves, but also drives the improvement of efficiency and green performance of the entire co-creation network through the capacity spillover effect. After core enterprises achieve dual improvements in production efficiency and green performance through AI, their efficient production management models and green standards are transmitted to upstream and downstream enterprises through the supply chain. This helps suppliers improve their production efficiency and low-carbon performance, thereby enhancing the green collaborative capacity of the entire supply chain and promoting enterprises to achieve green value co-creation. Therefore, this study proposes the following hypothesis:

H3: Artificial intelligence can enhance the Total Factor Productivity of manufacturing enterprises, thereby promoting their green value co-creation.

2.3. Moderating Roles of Financing Constraints and Corporate Influence

2.3.1. The Moderating Role of Financing Constraints

Financing constraints refer to an economic state where microeconomic entities such as enterprises, constrained by multiple factors including information asymmetry, agency conflicts, rigidity of transaction costs, and the external institutional environment during capital intermediation, face a significantly higher cost of external financing than internal financing. Alternatively, they struggle to obtain sufficient funds within a reasonable cost range to support investment projects with positive net present value. Financing constraints stem from financing frictions where the cost of external financing exceeds that of internal financing, which restricts enterprises' ability to allocate resources to high-investment and long-cycle projects [25].The moderating role of financing constraints is mainly reflected in the following three aspects: First, the impact of AI on green value co-creation is primarily attributed to its strong technical capabilities. Thus, the adaptability of AI technology to green demands becomes a prerequisite for its development, and the improvement of technical adaptability relies on the continuous innovation of AI technology. However, both the development of AI technology and the construction of a green value co-creation system require sufficient funds as strong support. Financing constraints will limit enterprises' access to funds, thereby affecting the development of their AI technology and green value co-creation. Second, the realization of green value co-creation mainly depends on multi-agent collaborative cooperation, data sharing, and real-time linkage, and the construction of inter-enterprise AI platforms is indispensable. Nevertheless, enterprises with high financing constraints are constrained by insufficient funds to bear the cost of building AI platforms, and sufficient funds are still needed as an indispensable cost for technology development in the process of achieving green value co-creation. Third, the ultimate goal of green value co-creation is to transform the results of collaborative creation into practical value, that is, to apply green technologies to actual production and management work. This process requires AI to support the large-scale implementation of technologies, and in applying green technologies to production, it is also necessary to adapt production lines to green technologies, which may incur costs related to production line optimization. Therefore, enterprises with high financing constraints are restricted by funds and cannot afford the expenditures required to transform green value co-creation results into practical outcomes. All these will weaken the promoting effect of AI on green value co-creation.

H4: Financing constraints play a negative moderating role in the impact of artificial intelligence on green value co-creation in manufacturing enterprises.

2.3.2. The Moderating Role of Corporate Influence

Corporate influence is an important manifestation of enterprises' market position, industry discourse power, social trustworthiness, and other related aspects [26]. Corporate influence is an important manifestation of an enterprise's market position, industry discourse power, social trustworthiness, and other relevant aspects. The stronger the corporate influence, the greater its ability to acquire and dominate external resources, and the better it can convey the credibility and reliability of engaging in green value co-creation to stakeholders. In addition, enterprises with strong influence can exert an industry benchmarking effect; conducting green value co-creation can convey the future development direction of the industry to the outside world, attracting more interest subjects to participate in green value co-creation. On the one hand, high-influence enterprises, by virtue of their market position, are more likely to obtain cross-industry and cross-link green data, providing high-quality samples for training AI algorithms. On the other hand, high-influence enterprises have rule-making power in the supply chain, enabling them to promote upstream and downstream enterprises to access AI collaboration platforms and enhance co-creation capabilities. Furthermore, the ultimate goal of green value co-creation is to transform co-created outcomes into economic value and ecological value. The brand trustworthiness of high-influence enterprises can reduce the market promotion costs of green products and shorten their conversion cycle. Therefore, this study proposes the following hypothesis:

H5: Corporate influence plays a positive moderating role in the impact of artificial intelligence on green value co-creation in manufacturing enterprises.

3. Research Design

3.1. Dependent Variable

The dependent variable in this study is green value co-creation (GVC). The core characteristic of GVC lies in multi-agent collaborative behaviors based on green goals within supply chains or industrial networks, and its essence is a process of resource integration and value coordination across enterprise boundaries, rather than the independent green practices of a single enterprise [27]. Existing studies show that academic measurements of value co-creation mostly focus on the characterization of cooperative relationships from a single dimension, such as using the concentration ratio of the top five customers to reflect the closeness of the connection between enterprises and their core partners [28]. In the field of green development, the number of green patent applications, as the core indicator for measuring enterprises' green technological innovation capabilities, has been widely used in studies related to enterprise green transformation and environmental performance [29], and its advantage lies in its ability to objectively quantify the actual inputs and outputs of enterprises in green technology R&D and application [30].However, the number of green patent applications by a single enterprise can only reflect the green development level at the individual enterprise level and cannot embody multi-agent collaborative interaction, which is the key feature distinguishing the independent development of enterprises from value co-creation. Based on this, considering the dual attributes of GVC—multi-agent collaboration and green goal orientation—this study refers to the measurement logic of inter-enterprise collaborative innovation proposed by scholars such as Di et al. (2024) and adopts the number of joint applications of green patents as the proxy variable for GVC

[31]. The rationality of this indicator is mainly reflected in two aspects: on the one hand, the number of joint applications of green patents directly reflects the resource sharing, technical collaboration, and goal coordination among at least two enterprises in the process of green technology R&D, which is consistent with the essence of multi-agent collaboration in GVC; on the other hand, the green attribute of green patents compared with other patents ensures that such collaborative behaviors are carried out around environment-friendly goals, accurately corresponding to the core demand of green orientation in GVC.

3.2. Core Explanatory Variable

The core explanatory variable in this study is AI. Currently, the academic community has formed a multi-dimensional measurement system for AI: Some scholars, from the perspective of technological innovation, use the number of enterprise AI-related patent applications to measure the intensity of technological input [32,33]; other studies focus on technology application scenarios and use the density of enterprise industrial robot applications to reflect the implementation level of AI in production links [34]; there are also literatures that, from the perspective of external environmental spillover, depict the impact of the regional AI ecosystem on enterprises through the number of AI-related enterprises in the city where the enterprise is located. However, the aforementioned measurement methods are limited to a single dimension and struggle to accurately capture enterprises' actual perception and application tendency of AI technology in operational decisions, while the application of AI at the enterprise micro-level is the focus of this study. Based on this, referring to the extraction logic of technical characteristics from enterprise textual information proposed by Yang, Y., An, R. & Song, J. (2025) and Yao, J.Q. et al. (2024) [35,36], this study adopts a hybrid method combining machine learning and text analysis to construct an enterprise-level AI measurement indicator. The specific steps are as follows:

1. Construction of the seed lexicon: Based on authoritative studies in the field of AI, multi-source authoritative lexical sources are integrated to form an initial seed lexicon. At the academic level, core terms defined in AI research by Yang et al. (2025) are referenced [37]; at the industrial practice level, key words for AI technology applications specified in the AI thesaurus provided by the World Intellectual Property Organization are adopted. Finally, 69 representative core seed words of AI are screened out.

2. Text Corpus and Model Training: Annual reports of listed companies during the research sample period are used as the text corpus. After word segmentation and stop-word removal processing via Python's Jieba tool, the preprocessed text data is input into the Skip-gram architecture of the Word2Vec model for training. By maximizing the co-occurrence probability of target words and context words, this model can effectively capture the semantic associations of words in specific contexts [38], providing a reliable vector representation foundation for subsequent semantic expansion.

3. Formation of the AI Dictionary: Based on the trained Word2Vec model, the cosine similarity between each initial seed word and other words in the corpus is calculated, and the top 10 extended words with the highest similarity are selected for each seed word. Subsequently, duplicate words and semantically deviant words are eliminated through manual review, ultimately forming a dedicated AI dictionary containing 187 words for this study.

4. Indicator Quantification: Based on the constructed AI dictionary, the word frequency statistics method is adopted to calculate the occurrence frequency of AI-related words in the annual reports of each listed company, which is used as the proxy variable for measuring enterprise AI. The advantages of this measurement method are as follows: on the one hand, as the core text disclosed by enterprises to the outside world, annual reports can truly reflect enterprises' attention to AI technology and actual application plans; on the other hand, the dictionary construction process through semantic expansion and manual screening effectively avoids the one-sidedness of single keyword retrieval, improving the coverage and matching degree of the indicator to the connotation of AI technology.

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3.3. Mediating Variables

The mediating variables in this study are technology spillover and total factor productivity. Referring to the studies of Jaffe, A.B. & de Rassenfosse, G. (2017) and Bloom, N., Schankerman, M. & Van Reenen, J. (2013), TS is measured by the number of citations of enterprises' patent technologies, processed by adding 1 and taking the logarithm [39,40]. TFP_OP is calculated using the Olley-Pakes method with reference to the study of Coomes et al. (2019) [41].

3.4. Moderating Variables

The moderating variables in this study are financing constraints and corporate influence. Referring to the study of Xu et al. (2020), KZ is measured using the enterprise financing constraint KZ index [42]. Corporate influence is measured by the ratio of the enterprise's annual main business income to the total main business income of its industry, processed by adding 1 and taking the logarithm.

3.5. Control Variables

Referring to the study of Jiang et al. (2025) [43], this study selects the following control variables: Total Assets (SIZE), Return on Total Assets (ROA), Proportion of Independent Directors (INDEP), Ownership Concentration (TOP), Management Shareholding Ratio (MEOR), Tobin's Q (TOBINQ), and Enterprise Scale (STAFF). The definition of each variable is shown in Table 1.

Table 1. Variable Definitions.

Variable Type	Variable Symbol	Variable Name	Variable Description
Dependent Variable	GVC	Green Value Co-creation	Ln(number of joint green patent applications + 1)
Explanatory Variable	AI	Artificial Intelligence	Ln(total word frequency + 1)
Mediating Variables	TS	Technology Spillover	Number of citations of enterprise patents
	TFP_OP	Total Factor Productivity	Olley-Pakes (OP) method
Moderating Variables	KZ	Financing Constraints	KZ index
	CMI	Corporate Influence	Ln(Enterprise's annual main business income / Total main business income of the industry in the same year)
Control Variables	SIZE	Total Assets	Ln(total assets in the current year)
	ROA	Return on Total Assets	Net profit / average balance of total assets
	INDEP	Proportion of Independent Directors	Number of independent directors / total number of directors
	TOP	Ownership Concentration	Shareholding quantity of the top 5

			shareholders / total share capital
	MEOR	Management Shareholding Ratio	Shareholding quantity of directors, supervisors and senior management / total share capital
	TOBINQ	Tobin's Q	(Circulating market value + non-circulating shares × net asset per share + book value of liabilities) / total assets
	STAFF	Enterprise Scale	Total number of employees

3.6. Model Construction

To examine the impact of artificial intelligence on enterprises' green value co-creation and its influencing mechanism, this study constructs the following regression models. Among them, Model 1 is used to test Hypothesis 1, Models 2 and 3 are used to test the mediation effect hypotheses, and Models 4 and 5 are used to test the moderation effect hypotheses.

$$GVC_{i,t}=\varrho_1+\beta_1 AI_{i,t}+\gamma_1 X_{i,t}+year_t+\delta_i+\alpha_1 \quad (1)$$

$$M_{i,t}=\varrho_2+\beta_2 AI_{i,t}+\gamma_2 X_{i,t}+year_t+\delta_i+\alpha_2 \quad (2)$$

$$GVC_{i,t}=\varrho_3+\beta_3 AI_{i,t}+\theta_1 M_{i,t}+\gamma_3 X_{i,t}+year_t+\delta_i+\alpha_3 \quad (3)$$

$$GVC_{i,t}=\varrho_4+\beta_4 AI_{i,t}+\varphi_1 KZ_{i,t}+\omega_1 AI\times KZ_{i,t}+\gamma_4 X_{i,t}+year_t+\delta_i+\alpha_4 \quad (4)$$

$$GVC_{i,t}=\varrho_5+\beta_5 AI_{i,t}+\varphi_2 KZ_{i,t}+\omega_2 AI\times KZ_{i,t}+\gamma_5 X_{i,t}+year_t+\delta_i+\alpha_5 \quad (5)$$

Enterprises are denoted by i and time by t. $GVC_{i,t}$ represents enterprises' green value co-creation, $AI_{i,t}$ denotes the development level of enterprises' artificial intelligence, $M_{i,t}$ stands for mediating variables, and $X_{i,t}$ represents control variables. $Year_t$ denotes year fixed effects, δ_i indicates individual fixed effects and α denotes the error term.

3.7. Data Source

This study takes listed manufacturing companies in China's Shanghai and Shenzhen A-share markets from 2015 to 2024 as the research object, with data sourced from CSMAR, CNRDS, annual reports of listed companies, etc. The data are processed as follows: (1) Exclude ST, *ST, and PT companies; (2) Exclude financial industry companies; (3) Eliminate samples with severe data missing; (4) Perform winsorization at the 1% and 99% levels. Finally, a total of 21,285 samples are obtained.

4. Empirical Results and Analysis

4.1. Descriptive Statistical Analysis

Table 2 reports the descriptive statistical results of each variable in this study. As shown in Table 2, the mean value of AI is 4.999, with a standard deviation of 0.784, a minimum value of 3.258, and a maximum value of 7.052. This indicates that there are significant differences in the level of AI development among sample enterprises, and the AI development level is unbalanced across enterprises. For the dependent variable GVC, the mean value is 0.135, the standard deviation is 0.463, the minimum value is 0, and the maximum value is 2.708. This shows that there are remarkable differences in green value co-creation among enterprises: some enterprises may not have carried out relevant practices yet, while others have achieved prominent results in this field, suggesting that Chinese enterprises have great room for improvement in green value co-creation. Regarding control variables: SIZE reflects the distribution of sample enterprises in terms of total assets; ROA indicates that some sample enterprises are facing certain profitability pressure; TOP shows that the shareholding ratio of the top five shareholders is relatively concentrated in some enterprises; TOBINQ reflects the differences in enterprises' market value expectations; MEOR illustrates that the intensity of management shareholding incentives varies across enterprises; STAFF reflects the distribution of the total number of employees among sample enterprises.

Table 2. Descriptive Statistical Analysis.

Variable	Obs	Mean	Std.Dev.	Min	Max
AI	21285	4.999	.784	3.258	7.052
GVC	21285	.135	.463	0	2.708
SIZE	21285	22.117	1.157	20.04	25.726
ROA	21285	.045	.07	-.243	.235
INDEP	21285	.379	.054	.333	.571
TOP	21285	.533	.148	.203	.864
TOBINQ	21285	2.122	1.331	.865	8.632
MEOR	21285	.179	.21	0	.71
STAFF	21285	7.63	1.143	5.17	10.792

4.2. Baseline Regression Analysis

Table 3 reports the baseline regression results of the impact of AI development on GVC of manufacturing enterprises. Column (1) presents the results when only the two core variables, AI and GVC are included, with firm and year fixed effects controlled. The results show that the estimated coefficient (0.039) of AI development on GVC of manufacturing enterprises is significantly positive at the 1% level. Column (2) adds control variables without fixing firm and year fixed effects; the estimated coefficient of the core explanatory variable AI is significantly positive at the 1% level, with a coefficient value of 0.074. Column (3) further incorporates firm fixed effects on the basis of Column (2), and the estimated coefficient of AI on GVC of manufacturing enterprises remains significantly positive at the 1% level, with a coefficient of 0.055. Column (4) includes year fixed effects on the basis of Column (3); the estimated coefficient of AI on GVC of manufacturing enterprises is still significantly positive at the 1% level, with a coefficient of 0.024. This indicates that for every 1% increase in the AI development level of manufacturing enterprises, the GVC level increases by 0.024%. The above results all verify Hypothesis 1, indicating that the positive driving effect of AI on the GVC of manufacturing enterprises is stable and reliable. Whether micro-level enterprise control variables are included, or firm-specific heterogeneity and macro-year shocks are controlled, the estimated coefficient of AI remains significantly positive at the 1% level. From the perspective of the mechanism, the core technical characteristics of AI are accurately responding to the key demands of GVC: on the one hand, AI's big data analysis and intelligent optimization capabilities can solve the information asymmetry among multiple subjects in co-creation, helping co-creation participants quickly reach a consensus on green goals and optimize the efficiency of collaborative resource allocation; on the other hand, AI's refined management and control of production processes can not only reduce the technical threshold and cost burden for enterprises to participate in green co-creation, but also provide quantifiable and traceable green achievement support for co-creation projects, thereby effectively activating enterprises' motivation and capability to participate in GVC. Regarding control variables, the larger the total assets of an enterprise, the more concentrated its ownership, the higher the matching degree between the market value and asset replacement cost of manufacturing enterprises, and the higher the management shareholding ratio, the higher the level of GVC of the enterprise.

Table 3. Baseline Regression Tests.

	(1)	(2)	(3)	(4)
	GVC	GVC	GVC	GVC
AI	0.039***	0.074***	0.055***	0.024***
	(4.802)	(18.723)	(7.704)	(2.919)
SIZE		0.109***	0.056***	0.027***
		(22.196)	(5.935)	(2.644)
ROA		0.043	-0.026	0.015
		(0.935)	(-0.605)	(0.338)
INDEP		0.150***	0.037	0.001
		(2.645)	(0.504)	(0.012)
TOP		-0.024	0.043	0.146***
		(-1.124)	(1.019)	(3.249)
TOBINQ		0.003	0.006**	0.007***
		(1.087)	(2.321)	(2.651)
MEOR		-0.046***	0.034	0.079**
		(-2.804)	(0.992)	(2.303)
STAFF		-0.008*	-0.004	0.016
		(-1.677)	(-0.400)	(1.509)
_cons	-0.058	-2.635***	-1.401***	-0.812***
	(-1.441)	(-30.144)	(-8.485)	(-4.415)
ID	YES	NO	YES	YES
Year	YES	NO	NO	YES
N	21285	21285	21285	21285
R^2	0.654	0.097	0.654	0.655
F	23.063	287.111	31.885	9.007

***p<0.01,**p<0.05,*p<0.10

4.3. Robustness Tests

4.3.1. Replacing the Core Explanatory Variable

Referring to the study by Cheng et al. (2024) [44], this study uses a text analysis method to measure the level of enterprise digital transformation (DT) as a replacement for the level of enterprise AI development. The regression results are presented in Table 4. Column (1) shows the regression results without including control variables, controlling for firm and year fixed effects; the coefficient of DT is 0.039, which is significantly positive at the 1% significance level. Column (2) reports the regression results after adding control variables to Column (1); the coefficient of DT is 0.029, also significantly positive at the 1% significance level. These results validate Hypothesis 1, indicating that the findings of the baseline regression are robust.

Table 4. Robustness Tests.

	(1)	(2)	(3)	(4)	(5)	(6)
	GVC	GVC	F.GVC	F2.GVC	GVC	GVC
DT	0.039***	0.029***				
	(5.386)	(3.914)				

AI			0.044***	0.026**		
			(4.798)	(2.431)		
L.AI					0.032***	
					(3.429)	
L2.AI						0.026**
						(2.482)
SIZE		0.027***		0.021	0.037***	0.038***
		(2.699)		(1.516)	(2.986)	(2.652)
ROA		0.014		0.142**	-0.029	-0.064
		(0.332)		(2.536)	(-0.582)	(-1.168)
INDEP		0.001		-0.023	-0.015	-0.015
		(0.015)		(-0.245)	(-0.180)	(-0.160)
TOP		0.147***		0.062	0.180***	0.194***
		(3.279)		(1.007)	(3.405)	(3.171)
TOBINQ		0.007***		0.010***	0.006*	0.005
		(2.641)		(3.219)	(1.662)	(1.175)
MEOR		0.076**		0.092*	0.063	0.024
		(2.207)		(1.885)	(1.511)	(0.476)
STAFF		0.015		0.003	0.011	0.014
		(1.471)		(0.191)	(0.917)	(0.956)
_cons	-0.025	-0.814***	-0.072	-0.514**	-1.026***	-1.034***
	(-0.836)	(-4.429)	(-1.591)	(-2.072)	(-4.608)	(-3.913)
ID	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES
N	21285	21285	17685	14562	17685	14562
R^2	0.655	0.655	0.682	0.712	0.683	0.712
F	29.004	9.860	23.020	5.046	8.060	5.459

***p<0.01,**p<0.05,*p<0.10

4.3.2. Lagged Dependent Variable

To effectively mitigate the potential bidirectional causal endogeneity between the dependent variable and the core explanatory variable, this study refers to the mainstream processing paradigm of existing literature and incorporates the lagged one-period and two-period values of the dependent variable (GVC) into the benchmark regression model. This approach aims to more accurately identify the causal effect of the core explanatory variable on the dependent variable and avoid estimation bias caused by the mutual influence between variables. Column (3) reports the regression results with the dependent variable lagged by one period, where the coefficient of AI is 0.044 and significant at the 1% level. Column (4) presents the regression analysis with the dependent variable lagged by two periods, showing that the AI coefficient is 0.026 and also significant at the 1% level. In summary, incorporating the lagged one-period and two-period dependent variables into the econometric model can effectively break the reverse causal chain between current variables, weaken the interference of bidirectional causal endogeneity on the estimation results, and provide a more reliable empirical basis for the accurate identification of the causal relationship between the core explanatory variable and the dependent variable. Hypothesis 1 is further verified, indicating that artificial intelligence can significantly promote corporate green value co-creation.

4.3.3. Lagged Core Explanatory Variable

To enhance the robustness of empirical results and the reliability of causal identification, this study addresses the potential endogeneity of the core explanatory variable. Meanwhile, considering that the impact of AI development on corporate green value co-creation may exhibit a time lag—affected by process factors such as technology adaptation and multi-agent collaboration—it may not manifest immediately in the current period but is more likely to unfold with a one-period or two-period lag. Thus, the core explanatory variable is treated with one-period and two-period lags. Column (5) reports the results with the core explanatory variable lagged by one period, and Column (6) presents those with a two-period lag, further verifying Hypothesis 1 of this study. This approach not only alleviates contemporaneous endogeneity interference through temporal separation to ensure the logical rigor of causal inference but also accurately captures the time-lag characteristics of AI development's impact on corporate green value co-creation. Through the comparative verification of coefficients across multiple lag periods, it provides dual support for the robustness and reliability of the research conclusions.

4.4. Mediating Mechanism

Test To verify the mediating mechanism hypotheses proposed earlier, this study draws on the research methods of Tingley et al. (2014) and Imai et al. (2010) [45,46] to explore the impact mechanism of AI development level on green value co-creation, with a focus on empirically testing the mediating effects of technology spillovers and TFP therein. The results are presented in Table 5. Column (1) shows that the AI development level significantly promotes technology spillovers in manufacturing enterprises at the 1% significance level. Column (2) reports the analysis of AI development level's impact on manufacturing enterprises' green value co-creation after incorporating the mediating variable of technology spillovers. The coefficient of AI decreases from 0.024 in the benchmark test to 0.023, while remaining significant at the 1% level, indicating that technology spillovers play a mediating role in the impact of AI on manufacturing enterprises' green value co-creation. This verifies Hypothesis H2, suggesting that AI drives spillover effects such as green technology knowledge sharing and green production experience diffusion among enterprises, reduces technical barriers and information costs for cross-agent green collaboration, and thus enables part of the AI dividends to be indirectly converted into green co-creation value through technology spillovers. Additionally, the fact that the coefficient does not drop to zero indicates that AI still exerts a direct promoting effect.

Column (3) indicates that the AI development level can significantly improve the TFP of manufacturing enterprises, with the coefficient of AI being 0.152 and significant at the 1% level. Column (4) presents the study on the impact of AI development level on manufacturing enterprises' green value co-creation after incorporating TFP as the mediating variable. The coefficient of AI decreases from 0.024 in the benchmark test to 0.023, while remaining significant at the 1% level, demonstrating that TFP plays a mediating role in the influence of AI on manufacturing enterprises' green value co-creation and verifying Hypothesis H3. This suggests that AI improves TFP by optimizing production processes and enhancing resource utilization efficiency. It not only reduces energy consumption and carbon emissions per unit of output for enterprises but also frees up financial, human, and other resources to support green collaboration projects. This enables part of the efficiency dividends of AI to be converted into green co-creation value, further improving the mechanism chain through which AI affects green value co-creation.

Table 5. Mediating Mechanism Tests.

	(1)	(2)	(3)	(4)
	TS	GVC	TFP_OP	GVC
AI	2.513***	0.023***	0.152***	0.023***
	(3.888)	(2.812)	(19.977)	(2.793)

TS		0.001***		
		(7.475)		
TFP_OP				0.037***
				(3.758)
SIZE		0.024**		0.008
		(2.375)		(0.655)
ROA		0.019		-0.053
		(0.438)		(-1.120)
INDEP		-0.003		0.000
		(-0.047)		(0.002)
TOP		0.155***		0.147***
		(3.458)		(3.286)
TOBINQ		0.006**		0.007**
		(2.251)		(2.458)
MEOR		0.076**		0.078**
		(2.215)		(2.256)
STAFF		0.015		0.023**
		(1.429)		(2.206)
_cons	10.347***	-0.756***	6.005***	-0.678***
	(3.198)	(-4.115)	(158.091)	(-3.619)
ID	YES	YES	YES	YES
Year	YES	YES	YES	YES
N	21285	21285	21285	21285
R^2	0.900	0.656	0.887	0.656
F	15.118	14.240	399.088	9.581

***p<0.01,**p<0.05,*p<0.10

4.5. Moderating Effect Test

Table 6 reports the results of the moderating effect tests for financing constraints and corporate influence. Column (1) presents the regression results without considering control variables under the condition of fixed individual and year effects. Column (2) shows the test results after adding the interaction term AI×KZ (AI and KZ index) and control variables. The coefficient of AI is 0.048, and the coefficient of AI×KZ is -0.046, both of which are significant at the 1% level. This indicates that financing constraints exert a significant negative moderating effect—specifically, for enterprises with high financing constraints, the promoting effect of AI development level on manufacturing enterprises' green value co-creation will be restricted. This further verifies Hypothesis H4 proposed earlier: even though AI itself can drive corporate green value co-creation, enterprises facing high financing constraints will struggle to fully allocate resources to adopt AI technologies and carry out green collaboration, ultimately weakening the positive role of AI.

To test Hypothesis H5 proposed earlier, Column (3) presents the regression results without considering control variables under the condition of fixed individual and year effects, where the coefficient of AI is 0.036 and significantly positive at the 1% level. Column (4) shows the test results after adding the interaction term AI×CMI (AI and Corporate Influence Index) and control variables. The coefficient of AI is 0.051, and the coefficient of AI×CMI is 0.023, both significant at the 1% level. This indicates that corporate influence exerts a significant positive moderating effect—specifically, for enterprises with strong influence, the impact of AI development level on manufacturing enterprises' green value co-creation is enhanced. This further verifies Hypothesis H5: enterprises

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with strong influence are more capable of integrating upstream and downstream resources, promoting the coordination of green standards, and attracting co-creation partners. They can more efficiently leverage AI technologies to implement green co-creation projects, thereby strengthening the promoting effect of AI on green value co-creation.

Table 6. Moderating Effect Tests.

	(1)	(2)	(3)	(4)
	GVC	GVC	GVC	GVC
AI	0.039***	0.048***	0.030***	0.051***
	(4.806)	(4.241)	(3.670)	(5.488)
kz	0.005	0.238***		
	(0.342)	(3.244)		
AI×kz		-0.046***		
		(-3.116)		
CMI			0.026***	-0.094***
			(5.346)	(-5.482)
AI×CMI				0.023***
				(6.964)
SIZE		0.029***		0.015
		(2.811)		(1.384)
ROA		0.005		-0.022
		(0.114)		(-0.498)
INDEP		0.000		-0.006
		(0.006)		(-0.086)
TOP		0.135***		0.111**
		(3.002)		(2.469)
TOBINQ		0.007***		0.006**
		(2.733)		(2.153)
MEOR		0.073**		0.056
		(2.122)		(1.626)
STAFF		0.016		0.012
		(1.511)		(1.166)
_cons	-0.060	-0.969***	0.021	-0.590***
	(-1.479)	(-5.079)	(0.491)	(-2.811)
ID	YES	YES	YES	YES
Year	YES	YES	YES	YES
N	21285	21285	21285	21285
R^2	0.654	0.656	0.655	0.656
F	11.589	8.275	25.840	12.907

***p<0.01,**p<0.05,*p<0.10

4.6. Heterogeneity Analysis

4.6.1. Voluntary Environmental Regulation

ISO 9001, as an internationally recognized environmental management system standard and a voluntarily adopted management tool by enterprises, provides a standardized pathway for enterprises' green management. Thus, it is reasonable to use it as a criterion to distinguish whether enterprises implement voluntary environmental regulations. The regression results of the heterogeneity analysis are presented in Table 7. Column (1) reports the results for ISO 9001-certified manufacturing enterprises, where the coefficient of AI is 0.031 and significant at the 5% level. Column (2) shows the results for non-ISO 9001-certified manufacturing enterprises, with the AI coefficient being 0.008 and not significant at the 10% level. It can be concluded that for manufacturing enterprises implementing voluntary environmental regulations, the level of AI development has stronger explanatory power for corporate green value co-creation. This result confirms that enterprises under voluntary environmental regulations can better exert the synergistic effect between institutions and technology. The standardized management framework established by ISO 9001 certification provides a foundation for AI to reduce application frictions and accurately empower green value co-creation. In contrast, non-certified enterprises lack such support, leading to fragmented green management. Consequently, AI struggles to break through coordination bottlenecks, and its driving effect on green value co-creation is not manifested.

Table 7. Heterogeneity Tests.

	(1)	(2)	(3)	(4)	(5)	(6)
	GVC	GVC	GVC	GVC	GVC	GVC
AI	0.031**	0.008	0.076***	0.014	0.032**	0.019**
	(1.978)	(0.727)	(3.220)	(1.638)	(1.961)	(1.978)
SIZE	0.024	0.036***	0.014	0.030***	0.028	0.030**
	(1.151)	(2.852)	(0.492)	(2.798)	(1.392)	(2.476)
ROA	0.043	-0.035	0.133	-0.027	-0.007	0.009
	(0.521)	(-0.649)	(1.029)	(-0.605)	(-0.081)	(0.177)
INDEP	-0.202	0.072	-0.126	0.096	-0.048	0.015
	(-1.537)	(0.764)	(-0.733)	(1.179)	(-0.328)	(0.176)
TOP	0.097	0.127**	-0.177	0.148***	0.156*	0.132**
	(1.130)	(2.228)	(-1.466)	(2.966)	(1.929)	(2.392)
TOBINQ	0.002	0.009***	0.012	0.005*	0.018***	0.004
	(0.467)	(2.638)	(1.590)	(1.830)	(3.039)	(1.390)
MEOR	0.004	0.105**	0.154	0.020	0.081	0.075*
	(0.068)	(2.271)	(0.504)	(0.595)	(1.104)	(1.905)
STAFF	-0.004	0.016	0.041	0.018*	0.019	0.014
	(-0.191)	(1.233)	(1.379)	(1.669)	(0.911)	(1.133)
_cons	-0.515	-0.956***	-0.714	-0.884***	-0.898**	-0.836***
	(-1.370)	(-4.114)	(-1.370)	(-4.520)	(-2.544)	(-3.757)
ID	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES
N	7646	13639	4701	16584	5694	15591
R^2	0.724	0.684	0.670	0.661	0.600	0.673
F	1.634	5.538	3.043	6.388	3.763	5.366

***p<0.01,**p<0.05,*p<0.10

4.6.2. Nature of Enterprise Ownership

Drawing on the classification of enterprise ownership, this study partitions the sample into state-owned enterprises (SOEs) and non-state-owned enterprises (non-SOEs) to conduct heterogeneity analysis, with results reported in Table 7. Column (3) presents the regression results regarding the impact of AI development level on green value co-creation for SOEs, where the coefficient of AI is 0.076 and statistically significant at the 1% level. Column (4) demonstrates that such a positive relationship is absent in non-SOEs. We conclude that compared with non-SOEs, SOEs exhibit a more pronounced capacity to translate AI development into green value co-creation. Specifically, on one hand, SOEs generally assume greater environmental governance obligations and demonstrate a stronger propensity to deploy AI technologies in key green value co-creation processes, such as green production optimization and carbon footprint tracing. On the other hand, the resource access advantages inherent in SOEs provide contextual support for AI to facilitate corporate green value co-creation, thereby further enhancing the efficiency of technology conversion.

4.6.3. Industry Attributes

To investigate the moderating role of industry attributes in the impact of AI on corporate green value co-creation, this study classifies the sample into high-polluting industries and non-high-polluting industries based on enterprise pollution intensity, and conducts a heterogeneity analysis, with the results presented in Table 7. Column (5) reports the impact of AI development on green value co-creation in high-polluting industries, where the coefficient of AI is 0.032 and statistically significant at the 5% level. Column (6) presents the results for non-high-polluting industries, showing that the AI coefficient is 0.019, also significant at the 5% level. In summary, for high-polluting industries, for every 1% increase in the level of AI development, green value co-creation increases by 0.032%. In contrast, for non-high-polluting industries, a 1% increase in AI development leads to a 0.019% increase in green value co-creation. Evidently, high-polluting industries exhibit stronger explanatory power regarding the role of AI in promoting corporate green value co-creation compared to non-high-polluting industries. Specifically, the coefficient for high-polluting industries (0.032) is approximately 68.4% higher than that for non-high-polluting industries (0.019). The underlying logic for this discrepancy lies in the fact that high-polluting industries are subject to more stringent environmental compliance requirements and greater pressure for green transformation, thereby generating a more urgent demand for green value co-creation initiatives such as emission reduction optimization in production processes and dynamic management of environmental risks. Meanwhile, the technical advantages of AI in scenarios including energy consumption monitoring, pollutant source tracing, and supply chain carbon footprint management exhibit a stronger alignment with the green transformation needs of high-polluting industries, thereby facilitating a more thorough release of technology-enabled effects.

5. Discussion and Research Prospects

5.1. Discussion

Compared with previous studies on AI and GVC that focus on e-commerce platform scenarios and emphasize subjective cognitive mechanisms [47], this study shifts its research perspective to the manufacturing sector an area with broader coverage and a core carrier of resource consumption and carbon emissions. It systematically reveals the objective transmission mechanism of AI empowering GVC, accurately addresses the practical pain points faced by manufacturing enterprises in the integration of AI application and GVC, and selects financing constraints and firm influence as moderating variables for empirical analysis in combination with the actual logic of enterprise development.

The research findings are as follows: First, AI development exerts a significantly positive promoting effect on GVC in manufacturing enterprises, and heterogeneity tests further reveal that this promoting effect is more prominent in voluntary regulation contexts, state-owned enterprises, and high-pollution industries. Accordingly, manufacturing enterprises should incorporate AI technology layout into the top-level design of their green development strategies, promoting the in-depth integration of AI with core business links such as production and manufacturing, supply chain collaboration, and green R&D. Meanwhile, enterprises under voluntary regulation can rely on AI technology to enhance the initiative of green innovation; state-owned enterprises need to give play to their advantages in resource integration and policy response to construct a mature demonstration model of AI and GVC; high-pollution industries should focus on the precise application of AI in emission reduction and carbon reduction, realizing the dual goals of environmental compliance and GVC through technological empowerment. Second, mechanism analysis confirms that AI can significantly enhance enterprises' technological spillover capacity and TFP, thereby improving the GVC level of manufacturing enterprises, that is, technological spillover capacity and TFP play a partial mediating role in the relationship between AI and GVC. Manufacturing enterprises should, on the one hand, optimize production processes through AI technology to reduce the resource and environmental costs per unit of output, consolidating the supporting role of TFP in GVC; on the other hand, establish an industrial chain-oriented AI technology sharing platform to promote the cross-enterprise and cross-departmental diffusion of core resources such as green process parameters and intelligent emission reduction schemes, amplifying the overall green collaborative effect of the industrial chain through technological spillover. Third, the results of moderating effect analysis show that financing constraints play a negative moderating role in the path of AI promoting GVC in manufacturing enterprises, while firm influence plays a positive moderating role, the greater the firm influence, the stronger the promoting effect of AI on GVC. Enterprises need to accurately align AI-driven green transformation projects with green financial instruments to enhance their competitiveness in financing channels such as green credit and green bonds. For enterprises with high influence, they should rely on their advantages in brand, channels, and resources, take AI empowered GVC practices as benchmarks, and lead upstream and downstream small and medium sized enterprises to participate in GVC by issuing industrial green standards and leading industrial chain green collaboration projects, forming a development pattern of leading enterprises driving and cluster linkage.

5.2. Research Prospects

Although this study has empirically examined the impact of AI on green value co-creation in manufacturing enterprises, it still has several limitations in certain aspects, which can serve as avenues for future research.

First, regarding sample selection and data dimensions. This study focuses on listed manufacturing companies on China's Shanghai and Shenzhen A-shares from 2015 to 2024. While it centers on the manufacturing sector—a core domain for green value co-creation—the sample is restricted to Chinese A-share listed enterprises, excluding non-listed companies and firms from other countries. This may limit the generalizability of the research findings. Meanwhile, the measurement of AI and green value co-creation in this study relies on corporate annual report texts and green patent data, lacking direct measurements of the depth of enterprises' AI technology application and the actual level of green value co-creation, which may lead to certain variable measurement bias. Future research could expand the sample scope to include non-listed companies and cross-country enterprises, and further improve the measurement system for AI and green value co-creation, thereby enhancing the accuracy and generalizability of the research.

Second, regarding mechanism exploration. Although this study investigates the mediating effects of technology spillovers and TFP, it fails to disentangle the internal heterogeneity of the mediating variables. For instance, technology spillovers can be more precisely categorized into horizontal and vertical technology spillovers, which may exhibit differences in both the strength and pathways of their impacts on the relationship between AI and green value co-creation in manufacturing enterprises. This also constitutes a promising avenue for future research.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
TFP	Total Factor Productivity
SOEs	State-owned Enterprises
GVC	Green Value Co-creation
SDGs	Sustainable Development Goals
ISO9001	International Organization for Standardization 9001

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