

Article

Can Artificial Intelligence Adoption Empower Digital–Green Synergy in Manufacturing Firms? Evidence from Large Language Models

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Abstract

Under the dual pressures of resource constraints and emission regulations facing global manufacturing, digital–green synergy transformation has become crucial to achieving sustainable economic development. However, the existing literature still lacks micro-level evidence on how artificial intelligence (AI) adoption drives digital–green synergy (DGS). This paper takes manufacturing listed companies from 2011 to 2022 as the research sample. Based on the BERT large language model, an index of enterprise AI adoption is constructed, and a two-way fixed effects model is used to empirically test the impact of AI adoption on digital–green synergy in manufacturing firms. The results show that AI adoption significantly enhances DGS in manufacturing firms, with stronger impacts in high-tech, non-heavy-polluting, and non-state-owned enterprises. The mechanism analysis indicates that AI adoption mainly promotes DGS in the manufacturing industry through three paths: expanding knowledge breadth, optimizing resource allocation, and breaking through organizational routines. Further analysis indicates that the positive effect of AI adoption is reinforced by executives' environmental backgrounds, while climate policy uncertainty exerts a dampening influence. Economic consequence tests confirm that improved DGS simultaneously enhances corporate social responsibility performance, fosters new-quality productivity, and strengthens supply chain resilience.

Keywords: AI adoption; digital–green synergy; manufacturing enterprises; impact channels; economic consequence



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1. Introduction

Digital–green synergy (DGS) in manufacturing firms is pivotal for driving high-quality societal development [1]. In recent years, governments around the world have placed great emphasis on DGS, continuously improving relevant policy frameworks [2]. In August 2024, the Cyberspace Administration of China and nine other departments jointly issued the Implementation Guidelines for Coordinated Transformation and Development of Digitalization and Greening, providing systematic policy guidance for traditional industries to accelerate their DGS transition. Against this backdrop, manufacturing—being a major source of pollution emissions and a core area for digital technology application—is central to

meeting the dual carbon goals. Therefore, focusing on manufacturing enterprises and deeply exploring the pathways of DGS transformation holds significant practical importance.

However, manufacturing enterprises face numerous obstacles in their DGS transformation at the practical level, which is constrained by the structural limitations in knowledge boundaries, resource allocation, and organizational capabilities. These obstacles often manifest as technological fragmentation, imbalanced resource investment, and organizational inertia, which together prevent digitalization investments from effectively supporting green objectives and leave green transformation without adequate systematic backing from digital technologies [3,4]. Although existing studies have explored the enabling role of digitalization on greening [5,6] and the traction effect of greening on digitalization [7,8], these studies mostly focus on one-way relationships rather than examining the deep integration of the two. A few studies have begun to examine DGS, but such studies remain descriptive, focusing on the characteristics of the collaborative phenomenon, without thoroughly analyzing its impact channels in manufacturing enterprises.

Artificial intelligence (AI) offers a new opportunity to address the dilemma of DGS in manufacturing firms. As a general-purpose technology, AI can permeate corporate operations, thereby reshaping the nexus of digitalization and greening [9]. Figure 1 documents the steady growth of AI-related patent filings in China in recent years. Different from general digital technologies that mainly remain at the functional levels, AI has more core capabilities such as data insight, intelligent decision-making, and system optimization [10], which can more targetedly alleviate the technical separation, investment imbalance, and conventional fixation in DGS. Therefore, AI is not only an important manifestation of the evolution of digital technologies, but also may become a key technical handle to break through the obstacles of DGS in manufacturing firms.



Figure 1. Trend of the number of AI patents in China.

The dynamic capability theory proposes that a firm's sustained competitive advantage stems from continuously perceiving external opportunities, integrating key resources, and reconfiguring organizational capabilities to adapt to the rapidly changing external environment [11,12]. The digital-green synergy in manufacturing also relies on the continuous enhancement of enterprises' capabilities in opportunity identification, resource integration, and organizational reconfiguration. First, AI can expand the breadth of enterprises'

cross-domain knowledge, strengthening their ability to recognize integration opportunities between digitalization and greening [13]. Second, AI can optimize enterprise resource allocation, promoting the coordinated use of digital and green resources [14]. Third, AI can drive the continuous optimization of organizational structure and organizational practices, enhancing the organizational capabilities of enterprises to adapt to DGS [15]. Therefore, the internal mechanism by which AI can enhance the level of DGS in manufacturing through expanding knowledge width, optimizing resource allocation, and promoting organizational reconfiguration remains to be further elucidated.

Based on the above analysis, this paper theoretically reveals the inherent logic of how AI adoption enhances DGS in manufacturing firms. This study uses the BERT large language model to construct AI adoption and conducts empirical tests using data from Chinese A-share manufacturing listed companies from 2011 to 2022. The research finds that AI adoption significantly improves the DGS in manufacturing firms, and this effect is more significant in high-tech, non-polluting, and non-state-owned enterprises. The mechanism analysis indicates that AI adoption can expand knowledge breadth, improve resource allocation, and break organizational conventions. The moderation effect analysis reveals that executives' environmental background strengthens the promoting effect, while climate policy uncertainty generates a restraining effect. Further analysis reveals that AI adoption significantly improves corporate social responsibility performance, fosters new quality productivity, and enhances supply chain resilience.

The marginal contribution mainly lies in three aspects. Firstly, this study uses the BERT large language model to construct indicators of AI adoption in manufacturing firms, which extend the measurement of existing research. Compared with indirect indicators such as recruitment data [16], the large language model method adopted can improve the accuracy of measurement. Secondly, this study incorporates DGS into the analytical framework of AI adoption, broadening the research boundaries of AI adoption. The current research on the economic effects of AI focuses on a single transformation perspective of digitization [17] or greening [18]. However, this paper integrates both perspectives into a unified analytical framework and theoretically analyzes how AI adoption can enhance DGS in manufacturing enterprises. Thirdly, this study reveals the mechanism by which AI adoption affects DGS in manufacturing firms. Unlike existing literature, which mostly explores the path of action from external perspectives such as digital finance development [19], based on the dynamic capability theory, this paper constructs an analytical framework and reveals the mechanism by which artificial intelligence promotes DGS from three dimensions: expansion of knowledge breadth, optimization of resource allocation, and reconfiguration of organizational routines.

2. Literature Review

As a strategic technology for industrial transformation, the research on AI has mainly focused on aspects such as indicator measurement and economic effects. In terms of indicator measurement, existing studies mostly use proxy variables such as enterprise annual report text feature analysis [20], employee resume data matching [16], and industrial robot density [21] to capture firm-level AI adoption. While these methods represent useful advances in measuring AI adoption, they are not without limitations. Text analysis relies on keyword dictionaries and inevitably involves subjective judgment. Similarly, resume data and robot density are imperfect proxies, as they do not adequately capture the substantive integration of AI into firms' operations. Patent applications, meanwhile, reflect innovation capacity more than actual usage and are subject to considerable time lags. These limitations may introduce measurement errors, thereby affecting the accuracy of subsequent empirical analysis.

Most existing literature explores the role of AI from various perspectives. Among these, digitalization [17] and greening [22] have emerged as two prominent research streams. In the digitalization aspect, enterprises can enhance their operations and organizational management by introducing AI to automate repetitive tasks [23]. In the greening aspect, AI adoption can improve energy efficiency and boost green innovation, thereby laying the foundation for the green transformation [22]. However, existing research is limited to a single transformation perspective of digitalisation or greening, lacking an overall perspective of the collaborative transformation in both aspects, and systematically examining the impacts generated by AI adoption.

Another strand of the literature focuses on the definition of DGS and the impact factors. In terms of the definition, existing studies generally define DGS as the collaborative evolution of digitalization and greening along both development goals and implementation paths [4]. Specifically, digital technology applications have significantly improved resource efficiency and environmental management capabilities, thereby supporting green development [24,25]. At the same time, the green agenda continuously shapes the direction of digital transformation, guiding digital technologies to fields such as energy structure transformation and resource recycling, thereby promoting green transformation [26,27]. In terms of influencing factors, existing studies are relatively limited, and only a few studies have explored the promoting effect of these factors from perspectives such as AI policies [28] and digital finance development [19]. Overall, the existing literature mostly stays at the theoretical level to explain the importance of DGS, while the empirical verification of its influencing factors is still insufficient.

In conclusion, although the existing literature has examined AI adoption and its impact on DGS, there are still the following limitations: First, regarding measurement, most existing studies rely on proxy variables such as the density of industrial robots, which do not adequately capture actual AI adoption and are prone to measurement errors. Second, in terms of research perspective, although existing literature has examined the effect of AI adoption on digitalization and greening separately, few studies examine the effect of AI adoption from the perspective of DGS. Third, in terms of mechanism analysis, existing studies have insufficient exploration of the mechanism by which AI adoption affects DGS; they fail to deeply clarify how AI adoption facilitates DGS in manufacturing firms through cognitive empowerment, resource activation, and organizational reshaping.

3. Theoretical Analysis and Research Hypothesis

3.1. *The Direct Effect of AI Adoption and DGS*

Digital–green synergy (DGS) in manufacturing refers to the coupled and mutually reinforcing interaction between digital transformation and green transformation strategies [4]. The essence of DGS lies in the complementary relationship between digitalization and greening. According to technological complementarity theory, different technologies or activities, through mutual supplementation and coordinated configuration, can generate incremental benefits beyond the input of a single factor, achieving an improvement in overall performance [29]. Digital transformation and green transformation, as two strategic paths for high-quality development, are not independent parallel activities but strategic activities with significant complementarity [30]. AI adoption has advantages such as data analysis, intelligent decision-making, and autonomous optimization, and can simultaneously empower digital transformation and green transformation, providing unified technical support for the complementarity of the two strategies [28,31].

On one hand, AI adoption integrates multi-source data such as production, equipment, energy, and emissions, embedding green constraints such as energy consumption and pollution emissions into the digital decision-making processes of production schedul-

ing, equipment control, and process optimization, thereby further empowering green development with digital capabilities [32]. On the other hand, the green development goals provide clear optimization directions and application scenarios for AI, guiding enterprises to continuously improve data collection, algorithm design, and resource allocation methods, and promoting the deep application of digital technology in the field of green governance [33]. Thus, AI promotes the transformation of digitalization and greening from being relatively independent to mutual promotion and coordinated evolution, ultimately enhancing the level of digital–green synergy of manufacturing enterprises. Therefore, we propose the following:

Hypothesis 1. *AI adoption can enhance manufacturing firms’ DGS.*

3.2. The Indirect Effect of AI Adoption and DGS

According to dynamic capability theory, the sustained competitive advantage of an enterprise stems from its ability to perceive external environmental changes, integrate key resources, and reconfigure organizational capabilities to adapt to changing market conditions [11]. DGS in manufacturing involves the coordinated advancement of two major strategies: digitalization and greening. It requires enterprises to continuously integrate heterogeneous knowledge, coordinate diverse resource allocations, and constantly adjust organizational operations. Therefore, it is essentially a process of the continuous formation and exertion of dynamic capabilities. AI adoption can effectively enhance an enterprise’s ability to integrate knowledge, allocate resources, and reconfigure the organization, providing important support for the formation of the enterprise’s dynamic capabilities and thereby promoting DGS in manufacturing [34]. Accordingly, this paper analyzes the mechanism by which AI promotes DGS in manufacturing from three aspects: knowledge breadth, resource allocation, and organizational reconfiguration. The theoretical framework is shown in Figure 2.

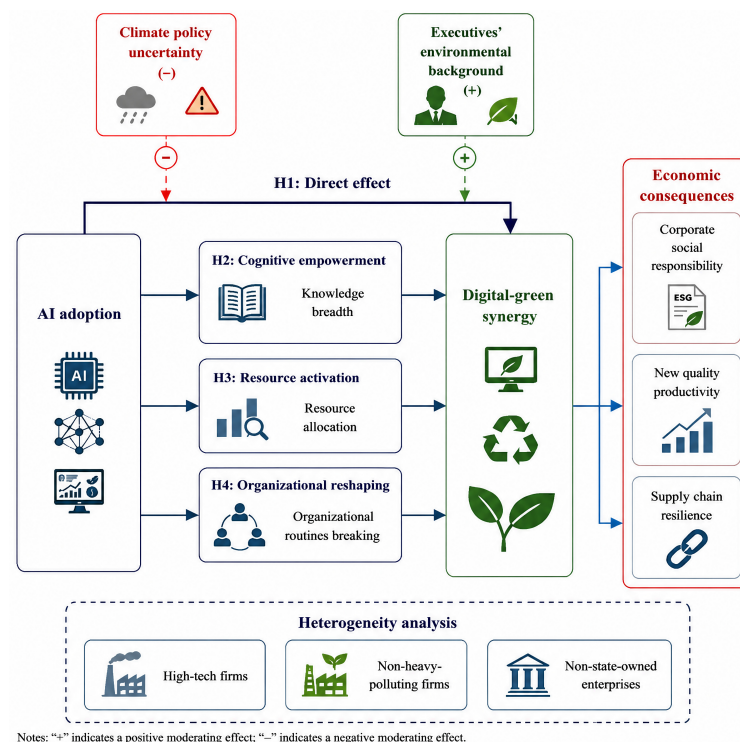


Figure 2. The theoretical framework.

3.2.1. Cognitive Empowerment Channel

The development of dynamic capabilities depends on firms' continuous acquisition, absorption, and integration of knowledge. Knowledge management research indicates that firms need not only to acquire external knowledge but also to recognize its potential value and integrate it with existing internal knowledge [35]. The absorptive capacity theory further emphasizes a firm's ability to identify, absorb, transform, and utilize external knowledge [36]. Digital–green synergy in manufacturing involves the cross-integration of knowledge across digital technologies, green technologies, and production management, thus placing higher demands on firms' capabilities for cross-domain knowledge acquisition and integration.

Traditional manufacturing enterprises evolve their knowledge structures along established technological trajectories, relying on unsystematic exploration for acquiring cross-domain knowledge, which limits their ability to identify opportunities for combining digital and green technologies. AI, through techniques such as text mining, semantic analysis, and association discovery [37], can systematically scan and analyze technical documents like patents and academic papers, constructing dynamic knowledge graphs covering digitization and greening domains. This transforms scattered and latent technological possibilities into searchable and inferable cognitive assets, enabling firms to continuously expand their knowledge boundaries and enhance knowledge breadth [38]. Increased knowledge breadth not only strengthens firms' comprehensive understanding of digital and green technologies but also promotes knowledge integration across different technological fields, providing a richer knowledge foundation for synergistic development in digitalization and greening [39]. Therefore, enhancing knowledge breadth contributes significantly to improving the digital–green synergy in manufacturing enterprises. Therefore, we propose the following:

Hypothesis 2. *AI adoption can expand knowledge breadth, enhancing manufacturing firms' DGS.*

3.2.2. Resource Activation Channel

The dynamic capability theory posits that the key to an enterprise's acquisition of competitive advantage is not merely having scarce resources, but rather continuously integrating resources in accordance with the external environment and strategic goals. Both digital transformation and green transformation require continuous investment of significant resources, yet there are differences in short-term returns and investment recovery cycles between the two. Digital projects typically have stronger visibility in terms of efficiency improvement, while the environmental benefits and long-term value of green projects are often difficult to fully demonstrate in the short term [40,41]. In situations where information is dispersed and decision-making capabilities are limited, enterprises may prioritize resource allocation to digital projects with higher short-term returns, resulting in a resource mismatch where digital facilities and green governance are separated, thereby weakening the synergy between digital and green [42].

AI can integrate multi-dimensional information such as production, finance, energy, equipment, and environment to enhance an enterprise's ability to identify resource demands and investment returns, and utilize predictive analysis and multi-objective optimization to compare different resource allocation schemes [43]. Compared to the traditional decision-making model relying on managers' experience, AI can incorporate production efficiency, energy consumption, pollution emissions, and long-term returns into the decision-making process, promptly identifying the incoordination between digital investment and green investment, and promoting the allocation of funds, technology, talents, and

equipment to projects that combine digital value and green value [44]. Thus, enterprise resource investment shifts from local, decentralized single-target allocation to overall allocation that considers both digital efficiency and environmental performance, providing stable resource guarantees for digital–green synergy in manufacturing firms. Therefore, we propose the following:

Hypothesis 3. *AI adoption can enhance resource allocation efficiency, enhancing manufacturing firms' DGS.*

3.2.3. Organizational Reshaping Channel

The dynamic capability theory holds that organizational restructuring is an important way for enterprises to achieve sustained competitive advantages. Organizational routines help reduce coordination costs and enhance operational efficiency, but they may also solidify existing technical paths and management logic, thereby becoming obstacles for enterprises to promote digital–green synergy transformation [45]. Existing studies have shown that overly relying on existing management routines can easily exclude exploratory activities, limiting an enterprise's ability to identify and utilize new opportunities [46,47]. Therefore, how to break the constraints of organizational routines has become a key issue for manufacturing enterprises to promote digital–green synergy.

The application of AI not only changes the way information is transmitted, decision-making patterns, and business processes of enterprises, but also promotes systematic adjustments to organizational structure and management systems [15]. By relying on algorithmic decision-making, AI can break through traditional hierarchical information barriers, promote data sharing and collaborative decision-making among departments such as production and R&D, thereby enhancing the cross-departmental collaborative efficiency of enterprises [48]. At the same time, AI drives enterprises to redefine job responsibilities, optimize business processes, and improve management systems, gradually breaking through the existing organizational routines formed by reliance on experience judgment and departmental division, providing organizational support for the coordinated promotion of digitalization and greening. As organizational structures and routines continue to be restructured, digital–green synergy can achieve cross-departmental collaboration under a unified organizational system, promote energy management, resource recycling, and pollution control, and ultimately promote the improvement of the digital–green synergy of manufacturing enterprises [49]. Therefore, we propose the following:

Hypothesis 4. *AI adoption can break through organizational conventions, enhancing manufacturing firms' DGS.*

4. Research Design

4.1. Data Sources

This paper takes the Chinese A-share manufacturing companies listed from 2011 to 2022 as the research sample. The enterprise financial data mainly comes from the CSMAR and Wind databases, and the annual report texts of listed companies are taken from the Juchao Information Network. During the sample selection process, this paper first excludes the samples of ST and *ST companies, then excludes the observations with less than one year of listing, and finally deletes the samples with missing key variable data. To alleviate the interference of extreme values on estimation, the upper and lower 1% of the continuous variables were trimmed. Finally, 11,188 valid observations are obtained.

4.2. Variable Selection

4.2.1. The Dependent Variable

The dependent variable is digital–green synergy (DGS). For digital transformation, this study follows Wu et al. [50] and sums up the frequency of digital-transformation-related keywords in annual reports, adds one, and takes the logarithm to measure firms' digital transformation. For green transformation, it follows Zhou et al. [51] and counts the frequency of green-transformation-related keywords in annual reports of listed firms, adding one before taking the logarithm to measure firms' green transformation. Subsequently, these two indicators are standardized, and a coupling coordination model is used to estimate DGS.

4.2.2. The Independent Variable

To measure firm-level AI adoption, this paper uses a large language model based on the BERT architecture to perform text analysis of the MD&A sections of listed firms' annual reports, constructing a firm-year index of AI adoption [52,53].

Step 1: Identification and extraction of AI-related texts. This paper first builds an AI technology keyword library, with keywords sourced from the Key Digital Technology Patent Classification System (2023) and related literature. Based on this keyword library, it selects sentences containing AI keywords from the MD&A text as the basic corpus for subsequent model training and prediction.

Step 2: Construction and annotation of the training set. To enhance the classification accuracy, 10% of the initially selected sentences are randomly selected as samples for manual annotation. The focus is on determining whether the sentences truly reflected the actual AI adoption by firms and identifying the specific technology types involved. For initial identification, this paper uses two large language models, ChatGPT (GPT-5) and ChatGLM (GLM-4.5). When the model predictions are inconsistent or questionable, we manually review the sentences to ensure annotation reliability.

Step 3: Supervised machine learning model training. To distinguish whether the AI keywords in the text represent actual AI adoption, this paper uses the BERT model for supervised learning. The annotated sentence samples are divided into training, testing, and validation sets in an 8:1:1 ratio. Through this training process, the model is enabled to have automatic discrimination ability for AI adoption sentences.

Step 4: Construction of the AI adoption indicator. Based on the trained BERT model, all the sentences to be predicted are automatically classified to identify whether the enterprise actually applied AI technology in that year. On this basis, this paper introduces a firm-year dummy variable for AI adoption, which equals one if the firm applied any type of AI technology in that year and zero otherwise.

4.2.3. Mechanism Variable

Knowledge Breadth (Td): Following Li et al. [54], we construct the knowledge breadth indicator based on the international patent classification group-level information of the firm's patents. This measure follows the Herfindahl index logic, capturing the variety and diversity of technological fields in which the firm holds patents. The larger the Td value, the more extensive the technical domains spanned by the firm's patents, indicating stronger knowledge integration and cross-border innovation capability.

Resource allocation (Ra): Referencing Ni & Wang [55], we first estimate a firm's reasonable investment level for a given year, and then measure resource allocation efficiency by overinvestment magnitude. A higher value indicates greater inefficiency in resource allocation.

Organizational Routines (Or): Following Yu-hua et al. [48], we use textual analysis to construct indicators of organizational routine breaking. Specifically, we count the frequency of keywords related to organizational routine breaking in all annual reports of listed firms, and measure the extent of organizational routine breaking for each firm by taking the logarithm of one plus the frequency.

4.2.4. Moderation Variable

Executive environmental background (Env): This paper defines a dummy variable that equals one if a firm has at least one executive with an environmental background in its executive team in a given year, and zero otherwise [27].

Climate policy uncertainty (Cpu): This paper measures climate policy uncertainty using the provincial-level index constructed by Ma et al. [56]. The index combines manual review with deep learning algorithms.

4.2.5. Control Variable

Referring to Zhao et al. [21] and Ke et al. [53], we control for a series of enterprise operating characteristics variables that might affect the green synergy level. Enterprise size (Size) is measured by the natural logarithm of the total assets at the end of the period. Profitability (ROA) is represented by the return on total assets. Financial leverage (Lev) is defined as the debt-to-equity ratio. Growth ability (Growth) is expressed by the growth rate of operating income. Board size (Board) is measured by the natural logarithm of the total number of board members. The proportion of independent directors (Indep) is represented by the number of independent directors at the end of the period divided by the total number of board members at the end of the period. Equity concentration (Top1) is measured by the shareholding ratio of the largest shareholder. The definitions and measurement methods are consistent with those in mainstream literature to ensure comparability and rigor. The detailed definitions of these variables are presented in Table 1.

Table 1. Definitions and measurement of variables.

Variable Type	Symbol	Variable Name	Measuring Method
Dependent variable	DGS	Digital–green synergy	Following Wu et al. [50] and Zhou et al. [51], the frequency of digital transformation and green transformation keywords in annual reports is counted, summed, and logarithmized, then standardized and estimated using a coupling coordination model.
Independent variable	AI	AI adoption	Using the BERT large language model to perform text analysis on MD&A sections of annual reports, a dummy variable equals 1 if AI technology is adopted in that year, and 0 otherwise.
Mechanism variables	Td	Knowledge breadth	Constructed based on the IPC group-level information of firms' patents, following the Herfindahl index logic.
	Ra	Resource allocation efficiency	Estimated by overinvestment magnitude following Ni & Wang [55]; a higher value indicates greater inefficiency.
	Or	Organizational routines breaking	Using textual analysis to count keyword frequency related to organizational routine breaking in annual reports, taking the logarithm of one plus the frequency.

Table 1. Cont.

Variable Type	Symbol	Variable Name	Measuring Method
Moderation variables	Env	Executive environmental background	A dummy variable equals 1 if at least one executive with an environmental background exists in the executive team, and 0 otherwise.
	Cpu	Climate policy uncertainty	Measured using the provincial-level index constructed by Ma et al. [56], combining manual review with deep learning Algorithms.
Control variables	Size	Enterprise size	Natural logarithm of total assets at year-end.
	ROA	Profitability	Return on total assets.
	Lev	Financial leverage	Debt-to-equity ratio.
	Growth	Growth ability	Growth rate of operating income.
	Board	Board size	Natural logarithm of the total number of board members.
	Indep	Independent directors proportion	Number of independent directors divided by the total number of board members at year-end.
	Top1	Equity concentration	Shareholding ratio of the largest Shareholder.

4.3. Model Design

To explore the impact of AI adoption on DGS in manufacturing firms, we select the two-way fixed effect model as follows:

$$DGS_{it} = \alpha + \beta AI_{it} + \gamma Controls_{it} + firm_i + year_t + \varepsilon_{it} \quad (1)$$

The subscripts *i* and *t* index firms and years, respectively. DGS is the digital–green synergy, AI is the level of AI adoption, Controls represent the control variables, ε is the random error term, and year and firm represent the fixed effects of year and individual, respectively.

5. Empirical Results

5.1. Descriptive Statistics

Table 2 presents the descriptive statistics for the main variables. The mean of DGS is 0.261, with a standard deviation of 0.221, a minimum value of 0, and a maximum value of 0.592. This indicates that there are significant differences in the digital–green synergy levels among different enterprises within the manufacturing industry. Additionally, compared with the existing related literature, it shows a high degree of consistency.

Table 2. Descriptive statistics.

Variable	Observation	Mean	Median	SD	Minimum	Maximum
DGS	11,188	0.261	0.353	0.221	0.000	0.592
AI	11,188	0.040	0.000	0.197	0.000	1.000
Size	11,188	22.015	21.921	0.994	20.121	24.683
ROA	11,188	0.042	0.043	0.048	−0.157	0.141
Lev	11,188	0.378	0.378	0.167	0.072	0.721
Growth	11,188	0.162	0.095	0.345	−0.509	1.608
Board	11,188	8.313	9.000	1.397	5.000	12.000
Indep	11,188	0.366	0.333	0.076	0.000	0.571
Top1	11,188	0.326	0.310	0.128	0.100	0.629

Note: This table presents summary statistics for the variables, all of which are defined in Table 1.

5.2. Baseline Regression Results

Table 3 presents the benchmark results of the impact of AI adoption on the digital–green synergy of manufacturing enterprises. Column (1) does not include enterprise-level control variables and only controls for the fixed effect of the year; columns (2)–(4) successively control for enterprise fixed effects and gradually add enterprise-level control variables. The coefficient of the AI adoption remains significantly positive at the 1% level. The results indicate that AI adoption has a positive impact on DGS and does not undergo substantial changes due to the introduction of control variables or adjustments to the fixed effect settings. Based on the estimation results in column (4) of Table 3, the coefficient of AI is 0.033, indicating that, under the condition that other factors remain unchanged, compared with enterprises that have not adopted AI, the average level of DGS of manufacturing enterprises that adopt AI increases by 0.033, accounting for approximately 12.64% of the sample mean.

Table 3. Baseline regression results.

	(1) DGS	(2) DGS	(3) DGS	(4) DGS
AI	0.112 *** (0.009)	0.038 *** (0.009)	0.045 *** (0.009)	0.033 *** (0.009)
Size			0.159 *** (0.007)	0.041 *** (0.008)
ROA			−0.262 *** (0.054)	−0.066 (0.050)
Lev			−0.003 (0.027)	0.039 (0.024)
Growth			−0.007 (0.007)	−0.000 (0.006)
Board			−0.016 *** (0.003)	−0.004 (0.002)
Indep			−0.117 *** (0.029)	−0.077 *** (0.026)
Top1			−0.281 *** (0.051)	−0.009 (0.043)
Constant	0.257 *** (0.000)	0.260 *** (0.000)	−2.957 *** (0.160)	−0.589 *** (0.170)
Firm FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes
Adj R ²	0.343	0.552	0.496	0.625
N	11,188	11,188	11,188	11,188

Notes: *** $p < 0.01$. The values in parentheses represent the standard errors clustered at the enterprise level, and the same applies below. All variables are as defined in Table 1.

The potential economic explanation lies in the application of AI in information integration capabilities in corporate strategic decision-making, enabling enterprises to break through the traditional reliance on experience-based judgment and to coordinate digital and green transformation more systematically [57]. Compared to traditional information systems, which mainly serve a single production or management process, AI can support enterprises in coordinating efficiency improvement and green development goals at the strategic level, making digital construction more focused on green performance, and green transformation can make fuller use of the information advantages brought by digital technology [58]. Thus, in the process of promoting digitalization and greening, enterprises gradually shift from relatively independent planning and implementation to collaborative

planning and implementation, ultimately promoting the continuous improvement of the DGS in the manufacturing sector. Therefore, Hypothesis 1 is verified.

5.3. Endogeneity Test

5.3.1. Instrumental Variable Test

Firstly, following Wu & Zhou [59], this paper selects the AI adoption probability in other enterprises of the same industry during the same period as the instrumental variable. On one hand, enterprises in the same industry usually face similar technological environments, market competition, and industrial policies. The adoption of AI by other enterprises within the industry can influence the decision of enterprises themselves to adopt AI through the demonstration effect, technology diffusion, and competitive pressure, meeting the requirement of relevance. On the other hand, the adoption of AI by other enterprises in the same industry does not directly affect the collaboration among sample enterprises, meeting the requirement of exclusivity. Table 4 reports the estimation results of the two-stage least squares method. In the first stage of column (1), the coefficient of the instrumental variable (IV) is significantly positive, and the LM statistic and F statistic both confirm the validity of the IV. In the second stage of column (2), the coefficient of AI is significantly positive, further confirming that the adoption of AI can enhance the collaboration level of manufacturing enterprises.

Table 4. IV test results.

	(1) AI	(2) DGS	(3) DGS	(4) DGS
IV	0.400 *** (0.075)		0.084 (0.052)	
AI		0.238 * (0.136)	0.029 *** (0.052)	[0.562, 1.382]
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	10,752	10,752	10,752	10,785
LM statistic	27.348 ***			
Wald F-statistic	28.470			

Note: *** $p < 0.01$, * $p < 0.1$. All variables are as defined in Table 1.

Secondly, to verify the rationality of the exclusivity assumption, this paper first conducts a semi-simplified regression, that is, directly including the instrumental variables into the OLS model. After controlling for the enterprises' application of AI and other control variables, it examines the impact of these variables on DGS in the manufacturing industry. The result of column (3) shows that the estimated coefficient of AI is significantly positive, while the estimated coefficient of the IV is not significant, providing preliminary support for the exclusivity assumption. The paper further refers to the Union of Confidence Intervals method proposed by Conley et al. [60] for robustness testing. It allows for a limited direct effect of the IV and re-estimates the parameter confidence intervals under this condition. Referring to the results of the semi-simplified regression, this paper sets the direct effect of the IV as $[-0.029, 0.029]$. The result of column (4) shows that the 95% confidence interval of the estimated coefficient of AI is $[0.862, 1.382]$, which does not include 0, indicating that the core conclusion has strong robustness to the exclusivity assumption.

Thirdly, the current study employs the Local-to-Zero method proposed by Conley et al. [60] for the test. This method assumes that the IV may have a direct effect close to zero and treats it as a random variable with a mean of 0 and a relatively small variance. Referring to the semi-simplified regression results, the mean μ is set to 0, and the variance is

set to $\omega = 0.0001$ based on the estimated standard error (approximately 0.01); at the same time, ω is set to 0.00009, 0.00008, and 0.00007 for sensitivity analysis. Figure 3 shows that under different variance settings, the estimated coefficient of AI changes very little, and the 95% confidence interval does not include 0. This further confirms that even under the condition of allowing a weak direct effect, the promoting effect of AI on DGS remains robust.

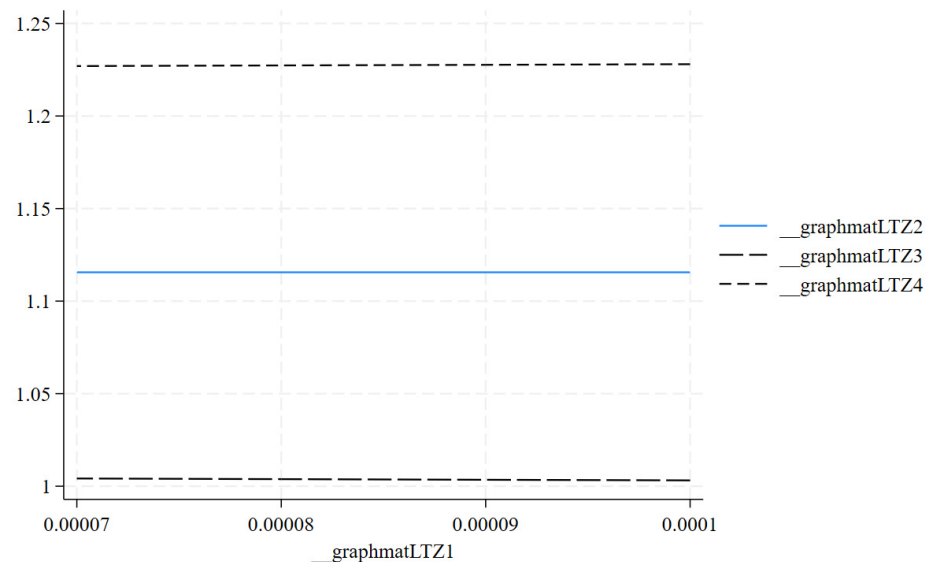


Figure 3. Coefficients and confidence intervals estimated based on the Local-to-Zero method.

5.3.2. PSM Test

AI adoption in manufacturing firms is not random. To alleviate potential self-selection bias, this paper adopts the propensity score matching (PSM) method [48]. Specifically, the sample is divided into a control and a treatment group. On this basis, 1:1 nearest neighbor matching is applied to reduce systematic differences in covariates. As shown in column (1) in Table 5, the coefficient on AI adoption remains significantly positive, confirming the results' reliability.

Table 5. Other endogeneity test results.

	(1) DGS	(2) DGS
AI	0.034 *** (0.009)	0.038 *** (0.0110)
Constant	−0.578 *** (0.170)	−0.806 *** (0.226)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Adj R ²	0.557	0.684
N	11,157	11,188

Note: *** $p < 0.01$. All variables are as defined in Table 1.

5.3.3. Entropy Balance Test

To mitigate the potential interference that an imbalance of covariates may bring to the estimation results, this paper draws on Hainmueller [61] and adopts the entropy balance method for the endogeneity test. This method adjusts the mean, variance, and skewness of the characteristic covariates of each sample individual, and then conducts weighted regression after the adjustment is completed. As shown in column (2) in Table 5, the

coefficient on AI adoption is significantly positive, indicating that the enhancing effect of AI adoption on DGS is robust.

5.4. Robustness Test

5.4.1. Replacing Explanatory Variable Lagged by One Period

Considering the possible lag between AI adoption and its generation of substantive impact, this study follows Chen et al. [62] and re-performs the regression with the explanatory variable lagged by one period (L_AI). As shown in column (1) in Table 6, the coefficient on L_AI remains significantly positive.

Table 6. Robustness test.

	(1) DGS	(2) DGS	(3) DGS	(4) DGS	(5) DGS	(6) DGS	(7) DGS	(8) DGS
L_AI	0.194 *** (0.014)							
DID		0.028 *** (0.010)	0.029 *** (0.010)					
AI				0.041 *** (0.009)	0.026 ** (0.011)	0.033 *** (0.008)	0.034 *** (0.009)	0.041 *** (0.009)
Constant	−0.153 (0.191)	0.260 *** (0.000)	−0.585 *** (0.172)	−0.898 *** (0.219)	−1.178 *** (0.260)	−0.589 *** (0.170)	−1.091 *** (0.246)	−0.916 *** (0.224)
Controls	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City*Year	No	No	No	No	No	No	Yes	No
Pro*Year	No	No	No	No	No	No	No	Yes
Adj R ²	0.610	0.552	0.557	0.534	0.597	0.557	0.540	0.535
N	8202	11,069	11,069	9386	11,100	11,188	8774	9363

Note: L_AI represents the lagged one-period term for the adoption of artificial intelligence; DID is a dummy variable for the policy in the artificial intelligence innovation application pilot zone. If the city where the enterprise is located is approved as a pilot and the policy is implemented in the current year or subsequent years, the value is 1; otherwise, it is 0. City*Year and Pro*Year represent the interaction fixed effects of city-year and province-year, respectively; *** $p < 0.01$, ** $p < 0.05$. The other variables are as defined in Table 1.

5.4.2. Considering the Impact of AI Policies

This paper employs the DID model to address potential endogeneity issues. Specifically, this paper regards the “Implementation Guidelines for the Construction of National New Generation Artificial Intelligence Innovation Development Pilot Zones” issued by the Ministry of Industry and Information Technology and other ministries as an exogenous shock, and examines its impact on DGS in manufacturing firms [28]. As shown in columns (2) and (3) in Table 6, the coefficients on AI adoption are all significantly positive. This further proves the research conclusion of this paper.

5.4.3. Adjusting the Sample Range

To eliminate potential estimation biases from the early stage of AI development, the starting point of the sample was adjusted to 2014, focusing on the sample of the rapid development of AI after the breakthrough of deep learning [48]. As shown in column (4) in Table 7, the coefficient on AI adoption remains significantly positive, and the results are still robust.

5.4.4. Replacing the Dependent Variable

This paper further conducts a robustness test by replacing the measurement of the DSG index. Specifically, to avoid the measurement bias that may be caused by a single measurement approach, we followed the research of Li and Lu [63] and re-constructed the proxy indicators for the digital and green transformation of enterprises. We also

recalculated the level of digital–green synergy using the coupling coordination degree model. The specific measurement indicators of each dimension after the replacement are shown in Table 7. The regression results are presented in the (5) column of Table 6. After changing the measurement method of the explained variable, the regression coefficient of AI remained significantly positive, further enhancing the robustness of the research conclusion.

Table 7. Comprehensive evaluation system for DGS.

Primary Indicator	Secondary Indicator	Measurement	Type	Symbol
Digital Transformation	Digital intangible assets	Digital-related intangible assets/total intangible assets	Input	+
	Digital economy patents	Number of digital economy patent applications	Output	+
Greening Transformation	Environmental investment	Environment-related construction in progress/total assets	Input	+
	Environmental expenditure	Environment-related expenses/operating revenue	Output	–
	Green innovation	Number of green patent applications	Output	+

Note: “+” indicates a positive impact, “–” indicates a negative impact.

5.4.5. Replacing the Explanatory Variable

To further examine the impact of the measurement method of the core explanatory variable on the research conclusion, this paper uses alternative indicators to re-measure the level of enterprise AI adoption. Referring to Cheng and Yang [64], considering that AI adoption requires the coordinated investment of software and hardware resources, this paper constructs the enterprise AI investment index from two dimensions: artificial intelligence software investment and hardware investment. Specifically, based on relevant literature and industry reports, this paper builds an AI keyword dictionary and uses Python 3.12.4 to perform text recognition to identify intangible assets and fixed asset investment projects related to artificial intelligence from enterprise financial reports. The sum of the two is obtained as the scale of enterprise AI assets, and further measures the intensity of enterprise AI investment by the proportion of artificial intelligence assets to total assets. The result in column (6) of Table 6 shows that the coefficient of AI remains significantly positive, further verifying the robustness of the conclusion.

5.4.6. Adding High-Dimensional Fixed Effects

To account for regional time-varying unobservables, this paper further incorporates interaction terms between cities and years, as well as between provinces and years, in the model. As shown in columns (7) and (8) in Table 6, after controlling for more stringent fixed effects, the coefficient on AI adoption remains significantly positive.

5.5. Mechanism Test

5.5.1. Cognitive Empowerment Channel

Column (1) of Table 8 shows that the coefficient of AI is significantly positive, with a Sobel Z statistic of 2.361. The confidence interval obtained by Bootstrap, repeated 500 times, is [0.0002, 0.0028], indicating that AI can significantly enhance DGS in manufacturing enterprises by expanding the breadth of enterprise knowledge. The potential economic explanations are that AI improves the enterprise’s ability to handle massive heterogeneous information and conduct cross-domain knowledge search, enabling the enterprise to obtain technical information outside its original knowledge system at a lower search cost and identify potential correlations between different knowledge domains, thereby breaking the constraints of existing technical paths on the scope of knowledge acquisition [37,38].

The expansion of knowledge breadth further enhances the enterprise's ability to identify green technology and digital technology collaboration opportunities, enabling cross-fusion of knowledge from different fields in product development, production, manufacturing, and environmental governance [39]. Existing studies have pointed out that the knowledge integration between digital and green technology can form a synergy effect beyond the application of a single technology, providing new technical combinations and innovation paths for enterprises to balance production efficiency and environmental performance, thereby promoting the transition from the relatively independent development of digitalization and greening to a coordinated evolution, and ultimately enhancing the digital–green synergy in manufacturing firms [65,66]. Therefore, Hypothesis 2 is verified.

Table 8. Mechanism test result.

Variables	(1) Td	(3) Ra	(5) Or
AI	0.054 *** (0.001)	−0.013 *** (0.004)	0.119 *** (0.032)
Constant	2.107 *** (0.258)	−0.666 *** (0.028)	−1.609 *** (0.347)
Sobel Z	2.361	−2.456	3.328
Bootstrap	[0.0002, 0.0028]	[−0.0022, −0.0002]	[0.0011, 0.0049]
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adj R ²	0.433	0.581	0.244
N	10,748	11,155	11,143

Note: Sobel Z is the test statistic for the mechanism test; the Bootstrap confidence interval is based on 500 repeated samplings; *** $p < 0.01$. The other variables as defined in Table 1.

5.5.2. Resource Activation Channel

Column (2) of Table 8 shows that the coefficient of AI is significantly negative, with a Sobel Z statistic of −2.456. The confidence interval obtained from Bootstrap, repeated 500 times, is [−0.0022, −0.0002], indicating that AI can significantly enhance DGS in manufacturing enterprises by improving resource allocation efficiency. The potential economic explanations are that AI can integrate multi-dimensional information such as production, finance, energy, and environment, enhance the enterprise's ability to identify resource demands and investment values, and improve the decision-making process of resource allocation through predictive analysis and intelligent optimization [43,67]. Further, AI can incorporate multiple goals into a unified decision-making framework, reduce information deviations and decision biases in the resource allocation process, and promote the flow of funds, technologies, and production factors to areas with both digital value and green value [44,68]. Therefore, AI helps to promote the transformation of enterprise resource allocation from decentralized and short-term allocation to a coordinated allocation model that takes into account both efficiency improvement and green development, providing a resource foundation for the integration of digitalization and greening. Therefore, Hypothesis 3 is verified.

5.5.3. Organizational Reshaping Channel

Column (3) of Table 8 shows that the coefficient of AI is significantly positive, with a Sobel Z statistic of 3.328. The confidence interval obtained by Bootstrap, repeated 500 times, is [0.0011, 0.0049], indicating that AI can significantly enhance DGS in manufacturing enterprises by breaking organizational conventions. The potential economic explanations are that AI drives enterprises to gradually shift from the traditional organizational model that

relies on hierarchical division of labor and experience management to a data-driven, cross-departmental collaborative organizational governance model [15]. This transformation not only strengthens the internal information flow and collaboration efficiency within the enterprise but also promotes cross-functional collaboration among different departments to make coordinated decisions around common strategic goals, reducing the constraints of organizational conventions on innovation activities and strategic adjustments [48]. As the organizational coordination ability continues to improve, digital construction and green development can be coordinated and advanced under a unified organizational system, enabling digital technology to more effectively serve green innovation and environmental governance, ultimately promoting the continuous improvement of digital–green synergy in manufacturing firms [49]. Therefore, Hypothesis 4 is verified.

5.6. Heterogeneity Test

5.6.1. High-Tech and Non-High-Tech Firms

This study divides the samples into high-tech and non-high-tech firms for group testing according to Zhu and Zhang [1]. As shown in columns (1) and (2) of Table 9, the positive promoting effect of AI adoption is significant for high-tech enterprises but is not statistically significant for non-high-tech firms. The underlying economic explanations are the fact that high-tech firms usually have stronger R&D capabilities and technical foundations, and can quickly absorb and integrate artificial intelligence technology, combining digitalization technology with the greening goal [69]. At the same time, these enterprises have more innovative talent pools, enabling them not only to proficiently apply AI but also to facilitate cross-departmental collaboration, thereby producing a more pronounced effect [70].

Table 9. Heterogeneity test results.

Variables	(1) High-Tech	(2) Non-High-Tech	(3) Heavy-Pollution	(4) Non-Heavy-Pollution	(5) State-Owned	(6) Non-State-Owned
AI	0.041 *** (0.010)	−0.019 (0.031)	−0.014 (0.031)	0.032 *** (0.011)	−0.002 (0.047)	0.044 *** (0.009)
Constant	−0.674 *** (0.195)	−0.613 (0.384)	−0.572 * (0.324)	−0.541 *** (0.207)	−0.836 * (0.366)	−0.602 *** (0.196)
<i>p</i> -value		0.038		0.037		0.046
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj R ²	0.554	0.566	0.600	0.549	0.593	0.555
N	8679	2048	2602	8113	1883	8533

Notes: The *p*-value is the empirical *p*-value obtained from 1000 Bootstrap repetitions for the test of the difference in coefficients between groups. *** $p < 0.01$, * $p < 0.1$. The other variables are as defined in Table 1.

5.6.2. Heavy-Pollution and Non-Heavy-Pollution Firms

This study divides the samples into heavy-pollution and non-heavy-pollution firms for group testing [71]. As shown in columns (3) and (4) of Table 9, the promoting effect of AI is significantly positive in the non-heavy-pollution firms sample but is not statistically significant for heavy-pollution firms. The underlying economic explanations are that non-heavy-pollution enterprises face relatively fewer environmental constraints and do not need to concentrate artificial intelligence resources on end-of-pipe treatment. In contrast, heavy-pollution enterprises are under compliance pressure and have to concentrate AI on response-oriented aspects such as pollution monitoring and meeting emission standards. This passive application mode not only hinders the penetration of AI into core business processes and strategic decisions [72].

5.6.3. State-Owned and Non-State-Owned Firms

This study divides the samples into two groups based on property rights for the purpose of conducting group tests [73]. As shown in columns (5) and (6) of Table 9, the promoting effect of AI adoption is significantly positive for the non-state-owned firms sample but is not statistically significant for the state-owned firms. The underlying economic explanations are that non-state-owned firms usually face more intense market competition, and their survival and development are strongly dependent on the continuous improvement of operational efficiency and innovation capabilities [74]. Conversely, state-owned firms bear policy and social responsibilities in their business goals, and their assessment system is multi-dimensional. Their response to the market signals and technological opportunities brought by AI is relatively slow, and their endogenous innovation motivation is significantly insufficient [75].

6. Further Analysis

6.1. Moderation Effect Analysis

6.1.1. The Moderation Effect of Internal Executives

According to the high-level team theory [76], the cognitive structure, professional experience, and value orientation of the executive team will profoundly influence the strategic choices of the enterprise. Executives with experience in the environmental field are not only more likely to form a commitment orientation towards sustainable development, but their environmental expertise and practical experience also constitute important human capital in the enterprise governance system, which helps to enhance the management team's ability to identify and judge environmental risks and green opportunities. Under these conditions, enterprises can more systematically incorporate ecological governance and long-term green transformation goals into the process of technological investment, resource allocation, and strategic decision-making [77]. To empirically examine this moderating effect, we construct an interaction term between AI and executives' environmental professional background (Env), and include it in our baseline regression model. As presented in Table 10, column (1), the coefficient on the AI $\times$ Env interaction term is significantly positive, indicating that executives' environmental background significantly boosts the impact of AI adoption on DGS in manufacturing firms.

Table 10. Moderating effect analysis results.

	(1) DGS	(2) DGS
AI	0.033 *** (0.009)	0.104 *** (0.036)
Env	−0.012 (0.009)	
AI $\times$ Env	0.028 ** (0.012)	
Cpu		0.007 (0.005)
AI $\times$ Cpu		−0.030 ** (0.0152)
Constant	−0.549 *** (0.174)	−0.603 *** (0.169)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Adj R ²	0.554	0.557
N	10,991	11,177

Note: *** $p < 0.01$, ** $p < 0.05$. The other variables are as defined in Table 1.

6.1.2. The Moderation Effect of External Climate Policy

The uncertainty of climate policies (Cpu) significantly affects AI adoption by altering the external institutional environment of firms. This policy uncertainty not only increases the institutional risks for enterprises during the green transformation process but also weakens the stable expectations of management regarding the intensity of future environmental regulations, green benefits, and compliance costs [78]. To test this moderating effect, this paper constructs an interaction term between AI and the Cpu. Column (2) of Table 10 shows that the coefficient of the interaction term is significantly negative, indicating that high Cpu significantly weakens the positive effect of AI. The underlying economic explanations are that the uncertainty of the policy environment significantly increases the institutional risks and compliance costs of green transformation, making enterprises more cautious or even delaying decisions when deploying AI adoption on DGS in manufacturing firms [79].

6.2. Economic Outcome Analysis

6.2.1. The Impact on Corporate Social Responsibility

Corporate social responsibility (CSR) is not only an important indicator of a company's sustainable development, but also a key factor for its social reputation and long-term competitiveness. In practice, some manufacturing enterprises, due to resource constraints or insufficient green governance capabilities, have unbalanced fulfillment of CSR. We use the corporate social responsibility index as the proxy variable for CSR, and take the lagged one-period DGS as the explanatory variable to investigate the impact of digital–green synergy among manufacturing enterprises [80]. As shown in column (1) of Table 11, the regression coefficient on L_DGS is significantly positive, indicating that the improvement in DGS significantly enhances the corporate social responsibility performance. The underlying economic explanations are that DGS strengthens the social value orientation of the enterprise, making it easier to identify and respond to the environmental and social demands of stakeholders, thereby enhancing the enterprise's sense of responsibility [81].

Table 11. Economic outcome test results.

	(1) CSR	(2) NQPF	(3) Resil
L_DGS	0.030 ** (0.015)	0.023 *** (0.003)	0.015 ** (0.007)
Constant	−0.335 (0.246)	−0.099 ** (0.050)	−0.053 (0.109)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adj R ²	0.582	0.576	0.525
N	8099	8116	7841

Note: L_DGS represents the lagged first-period term of the DGS; CSR stands for corporate social responsibility performance; NQPF is new quality productivity; Resil is supply chain resilience. *** $p < 0.01$, ** $p < 0.05$. The other variables are as defined in Table 1.

6.2.2. The Impact on Enterprises' New Quality Productive Forces

New quality productivity forces (NQPFs) are not only an important indicator for measuring an enterprise's technological innovation ability, resource allocation efficiency, and high-value-added output capacity, but also a key driver of high-quality development in manufacturing firms [82]. In traditional manufacturing enterprises, there are obstacles to the improvement of NQPF, such as low efficiency in converting innovation outputs and scattered R&D resources. We take new quality productivity as the dependent variable, and use the lagged one-period DGS as the explanatory variable to investigate the impact

of digital–green synergy in manufacturing [83]. As shown in column (2) of Table 11, the regression coefficient on L_DGS is significantly positive, indicating that the improvement of DGS significantly promotes the development of NQPF. The underlying economic explanations are that DGS further expands the high-value-added development path of enterprises, driving them to transform towards greening and high-endization. Through digital empowerment, enterprises can develop low-carbon products, build green service systems, and promote circular economy models [83].

6.2.3. The Impact on the Enterprise’s Supply Chain Resilience

Supply chain resilience (Resil) refers to the ability of an enterprise to maintain the continuity of its supply chain and quickly resume operations when facing uncertain shocks. The supply chain of manufacturing enterprises is prone to external disturbances such as environmental, policy, and market factors due to its numerous links, extensive outsourcing, and cross-regional operations, resulting in a relatively high risk of supply chain disruption. To test whether AI adoption can strengthen supply chain resilience through DGS among manufacturing enterprises, this paper, referring to Shunshan & Han [84], takes supply chain resilience as the dependent variable and uses the lagged one-period DGS as the explanatory variable. As shown in column (3) of Table 11, the regression coefficient on L_DGS is significantly positive, indicating it can enhance supply chain resilience. The underlying economic explanations are that DGS among manufacturing enterprises can achieve full-process visualization of the supply chain, enabling enterprises to quickly identify potential risks, optimize inventory and logistics scheduling, and enhance their sensitivity and response speed to external disturbances [85,86].

7. Conclusions and Implications

7.1. Conclusions

As a pivotal driver of the ongoing technological revolution and industrial transformation, artificial intelligence (AI) has emerged as a critical enabler of efficient, environmentally sustainable, and resilient manufacturing systems. This paper takes manufacturing listed companies from 2011 to 2022 as the research sample. Based on the BERT large language model, an index of enterprise AI adoption is constructed, and a two-way fixed effects model is used to empirically test the impact of AI adoption on digital–green synergy in manufacturing firms. Our findings robustly demonstrate that AI adoption significantly enhances DGS aimed at environmental performance improvement, and this result withstands extensive sensitivity and robustness checks. The mechanism tests show that AI mainly promotes the DGS through three paths: expanding the breadth of knowledge, optimizing resource allocation, and breaking organizational conventions. Heterogeneity analyses further show that executives’ environmental experience strengthens AI’s collaborative impact, whereas climate policy uncertainty attenuates it. Economic consequence tests confirm that AI-driven DGS yield multifaceted benefits: improved corporate social responsibility performance, stimulated new-quality productive forces, and enhanced supply chain resilience.

7.2. Discussion

7.2.1. Theoretical and Practical Implications

First, this paper provides a new research perspective for measuring AI adoption in enterprises. Existing studies mostly use indicators such as the density of industrial robots [21], job postings [16], or traditional text word frequency [20] to measure the level of artificial intelligence adoption in enterprises. These indicators often fail to fully reflect the actual penetration degree of AI in enterprise production and operation. Based on the BERT large language model, this paper identifies the semantic information related to AI in

enterprise annual reports and constructs enterprise-level indicators of AI adoption, which, to some extent, improves the semantic recognition ability of measurement.

Second, this paper incorporates the DGS into the analysis framework of AI adoption, expanding the theoretical understanding of the transformation effect of AI. Existing studies usually separately examine the impact of artificial intelligence on digitalization transformation [17] or greening transformation [18], but rarely focus on the complementary relationship between the two types of transformation. Our findings indicate that AI generates value not merely by advancing digitalization or greening alone, but by driving their deep integration through data integration, goal embedding, and multi-objective optimization, thereby enabling DGS. This finding expands the research on the economic effect of AI and further enriches the application of the complementary theory of technology in the context of manufacturing transformation [87].

Third, this paper shows that the value of AI not only lies in improving production efficiency and reducing operational costs, but also in promoting the deep integration of digitalization and greening. Therefore, manufacturing enterprises should elevate AI from a local production tool to a strategic enabler of coordinated digital–green development. In practice, firms should leverage AI’s strengths in data analytics and intelligent decision-making across key areas, including production, energy management, environmental governance, and business operations, to achieve synergistic improvements in both digital capabilities and green performance.

Fourth, the promotion of digital–green synergy by AI is not solely dependent on technological investment, but is based on the continuous improvement of enterprises’ dynamic capabilities. This paper finds that knowledge breadth, resource allocation, and organizational restructuring are important transmission paths for the effectiveness of artificial intelligence. This means that in promoting AI adoption, firms should not only strengthen digital infrastructure but also prioritize cross-domain knowledge integration, resource optimization, and organizational innovation. Such efforts can continuously strengthen the alignment between AI and business operations, fully unleashing its potential to drive digital–green synergy in manufacturing.

7.2.2. Limitations and Future Research

Although this paper conducts a relatively systematic analysis of how AI promotes the DGS in the manufacturing industry, there are still some limitations. Firstly, the research samples in this paper mainly come from Chinese A-share manufacturing listed companies. When applying the research conclusions to non-listed manufacturing enterprises, caution is still necessary. Listed companies generally perform better than non-listed enterprises in aspects such as corporate governance, financing ability, digital foundation, and information disclosure quality. Therefore, the mechanism of how AI promotes DGS and its impact degree may vary among different types of enterprises. Future research can further combine data from small and medium-sized enterprises, specialized and innovative enterprises, and non-listed manufacturing enterprises to test the applicability range of the research conclusions. Second, despite various robustness tests, this paper cannot eliminate concerns about omitted variables and reverse causality in causal identification. The above identification strategies provide relatively consistent empirical evidence for the conclusions of this paper, but they cannot eliminate all doubts about causal identification. Future research can combine quasi-natural experiments, policy shocks, or long-term tracking data from enterprises to further enhance the rigor of causal identification. Thirdly, this paper mainly focuses on the average effect of AI promoting digital–green synergy in manufacturing, but does not further examine the heterogeneity characteristics in different situations. For example, whether there are nonlinear or threshold effects in the application intensity of AI,

whether the uncertainty of climate policies has a phased impact, and how complementary conditions, such as organizational capabilities and digital infrastructure, affect the effect of AI need further research. In addition, future research can also try to adopt different measures for measuring climate policy uncertainty to further test the relevant conclusions and improve the robustness of the research conclusions.

7.3. Policy Implications

In light of these findings, we derive targeted policy recommendations for governments, industry regulators, and enterprise decision-makers. First, promote the coordinated deployment of AI and the DGS in the manufacturing industry. Relevant departments should incorporate artificial intelligence into the digital-green synergy policy framework, avoiding the separate implementation of digital transformation and green governance. Key scenarios such as energy management, production scheduling, equipment control, emission monitoring, and resource recycling can be utilized to build “AI + green manufacturing” demonstration projects, guiding enterprises to embed energy consumption and emission constraints into intelligent production decisions. At the same time, industrial data infrastructure and industry-level AI model libraries should be improved to promote the standardized collection and compliant sharing of production, energy, and environmental data. Through open-source algorithms and model-as-a-service models, the data and technology costs for enterprises to carry out digital-green synergy transformation can be reduced, fully releasing the system synergy effect of AI in knowledge expansion, resource optimization, and organizational restructuring.

Second, implement differentiated support policies based on enterprise heterogeneity. For high-tech enterprises, priority should be given to supporting their application of AI in cutting-edge fields such as low-carbon materials and intelligent energy management. Encourage them to lead the establishment of industrial innovation consortia and promote the formulation of industry-level green AI standards. For heavily polluting enterprises, promote the extension of AI from end-of-pipe pollution control to the entire process of energy efficiency diagnosis, carbon emission tracking, and clean production transformation, systematically enhancing their digital and green collaboration capabilities. For non-state-owned enterprises, measures such as improving intellectual property protection, expanding green technology financing channels, providing technical transformation subsidies, and tax incentives can be adopted to strengthen their innovation incentives. These efforts can help convert their inherent flexibility and rapid response capabilities into a key driving force for DGS. For state-owned enterprises, it is necessary to improve the performance evaluation and management incentive mechanisms for DGS, and enhance the efficiency of AI adoption.

Third, strengthen the green governance capabilities of senior executives and the construction of comprehensive human capital. Research shows that the environmental background of senior executives can significantly strengthen AI's positive impact on DGS. Therefore, enterprises should include managers with experience in environmental management and green technology in the process of formulating AI strategies, choosing technical routes, and allocating resources, to enhance their influence in the selection of technical routes and resource allocation. For enterprises lacking relevant talents, a digital-green transformation committee can be established, and professional training for senior executives in artificial intelligence, carbon management, and green governance should be strengthened to enhance their systematic understanding and execution ability of the integration of green development. At the same time, environmental performance and the effectiveness of green development integration should be included in the evaluation system of AI projects, to

avoid enterprises only measuring the application effect of AI based on short-term efficiency and cost reduction.

Fourth, enhance the stability, transparency, and predictability of climate policies. The uncertainty of climate policies would weaken enterprises' willingness to invest in AI and the synergy effect of green development. Therefore, relevant departments should establish clear emission reduction targets for the medium and long term, along with binding constraints for key industries and phased implementation roadmaps, to reduce investment hesitation caused by frequent policy adjustments. For policies with a significant impact range, set a reasonable transition period and respond promptly to enterprises' concerns through consultation, policy communication channels, and regional pilot mechanisms, enhancing enterprises' ability to adapt to policy changes. In addition, policy support should be aligned with the longer investment recovery period of AI projects, ensuring the continuity of green credit, fiscal subsidies, and tax incentives. This would reduce the risk of firms abandoning DGS projects due to policy shifts, thereby reinforcing the sustainability and effectiveness of AI-driven digital–green synergy.

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