

Article

How Artificial Intelligence Influences the Green Transformation of Manufacturing Enterprises: A Dynamic Capabilities Perspective

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Abstract

As a strategic general-purpose technology reshaping the manufacturing landscape, artificial intelligence (AI) holds significant potential to drive green transformation. However, how AI translates into green transformation through organizational capabilities has received limited attention. This study examines how AI drives green transformation in manufacturing enterprises through dynamic capabilities—specifically, absorptive, innovative, and adaptive capabilities. Drawing on the resource-based view and dynamic capabilities theory, we develop a theoretical framework positioning these capabilities as the core mediating mechanisms. Using panel data from Chinese manufacturing firms (2012–2023) and text mining with fixed-effects models, we find that AI significantly accelerates green transformation. Mechanism analysis confirms that dynamic capabilities mediate this relationship through three pathways: enhancing absorptive capability, stimulating innovation capability, and improving adaptive capability. Heterogeneity analysis reveals that the effect is stronger in non-state-owned, large-scale, and non-high-tech firms, suggesting that institutional and resource contexts shape AI's impact. This article provides micro-level evidence on AI-driven green transformation in manufacturing enterprises from the dynamic capabilities perspective, offering theoretical and practical insights for advancing high-quality transformation of China's manufacturing sector in the digital-intelligent era.

Keywords: artificial intelligence; green transformation; dynamic capabilities; corporate social responsibility; sustainable development; manufacturing firms

1. Introduction

Amid the intertwining of the global technological revolution and climate change, promoting the intelligent and green transformation of manufacturing has become a global consensus and a key part of China's national strategy. In December 2024, the Central Economic Work Conference emphasized the need to “actively apply digital and green technologies to upgrade traditional enterprises.” The 2025 “Proposal of the CPC Central Committee on Formulating the 15th Five-Year Plan for National Economic and Social Development” further stressed “adhering to intelligent, green, and integrated development to accelerate the building of a manufacturing powerhouse”. Given China's dual role as the world's largest manufacturing economy and a major carbon emitter, the country provides an ideal empirical setting for examining how AI drives green transformation in manufacturing enterprises. In this context, artificial intelligence—as a new-generation general-purpose technology—has become a critical driver of technological innovation and industrial transformation [1]. Manufacturing enterprises, being recognized as a major contributor to carbon emissions and energy consumption in China, present a green transition



Academic Editor: Jiang Wu

Received: 23 May 2026

Revised: 30 June 2026

Accepted: 6 July 2026

Published: 16 July 2026

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that is not only directly linked to the achievement of the “dual carbon” goals but also provides an urgent and representative research context for leveraging artificial intelligence to drive this transition.

Existing studies on AI and corporate environmental outcomes have developed along three streams. The first stream examines the direct effects of AI on environmental performance. Empirical evidence indicates that AI adoption significantly promotes green innovation [2,3], enhances environmental performance [4], and facilitates industrial transformation [5,6]. However, these studies predominantly treat firms as passive recipients of technology, with limited attention to the organizational processes through which AI translates into environmental benefits. The second stream investigates the mediating mechanisms through which AI affects environmental performance. Researchers have identified pathways such as operational capabilities [7], R&D investment [8], and green commitments [9]. Recent studies have further recognized AI's enabling effects on carbon neutrality performance [10] and its moderating role in ESG performance transformation [11]. While these studies acknowledge that AI's impact operates through intermediate organizational factors, they tend to conceptualize these mediators as static variables rather than dynamic process that evolve in response to environmental pressures. Consequently, how firms systematically build and leverage organizational capabilities to address environmental challenges remains insufficiently explained. The third stream adopts a dynamic capabilities perspective. This literature increasingly recognizes green transformation as a systemic process requiring firms to continuously reconfigure resources and capabilities in response to evolving environmental pressures [12–14]. Dynamic capabilities, defined as a firm's ability to integrate, build, and reconfigure resources to address rapidly changing environments [15], have been identified as critical drivers of corporate green transformation [16–18]. However, existing studies have primarily examined the role of dynamic capabilities in general green transformation contexts or specific green innovation outcomes, without systematically investigating how AI enhances dynamic capabilities to drive green transformation. In particular, the distinct roles of absorptive capability, which refers to a firm's ability to acquire, assimilate, transform, and apply new information and knowledge [19]; innovative capability, which refers to a firm's ability to develop new products and processes, and business models [20]; and adaptive capability, which refers to a firm's competence to reconfigure internal resources and routines in response to dynamic environmental conditions [21], as parallel mediating mechanisms in the AI–green transformation nexus remain unclear.

Therefore, this study adopts dynamic capabilities as its core analytical lens to explore how AI enables green transformation by empowering manufacturing firms' dynamic capabilities and their subsystems—absorptive, innovative, and adaptive capabilities. To address this question, we examine listed Chinese manufacturing firms from 2012 to 2023, using text analysis, panel data models, and mechanism testing to empirically investigate AI's impact on green transformation and its underlying pathways. This paper aims to show that AI is not merely a technical tool but a key enabler that reshapes corporate dynamic capabilities and facilitates systemic transformation. Our findings offer new theoretical insights into the synergy between digitalization and greening, while providing empirical evidence and policy recommendations for firms seeking sustainable competitive advantages and for governments designing coordinated technology–environment policies.

The main contributions of this paper are as follows. First, by establishing a theoretical link between AI and green transformation, we advance the dynamic capabilities literature and demonstrate how AI, as an external driver, enhances firms' absorptive, innovative, and adaptive capabilities. Second, it empirically validates the mediating roles of these three capabilities, clarifying the distinct pathways through which AI translates into green

transformation, whereas prior research has largely treated these mechanisms as a static black box without distinguishing the parallel mediating effects of absorptive, innovative, and capabilities. Third, it examines how contextual factors, including ownership type, firm size, and industry technology level, moderate the effectiveness of AI-enabled dynamic capabilities, and identifies the boundary conditions of these effects, offering implications for differentiated policy design.

The remainder of this study is structured as follows: Section 2 presents the theoretical foundation and research hypotheses; Section 3 outlines the research design; Section 4 conducts empirical analysis; and Section 7 offers conclusions and implications.

2. Theoretical Framework and Research Hypotheses

Corporate green transformation refers to a sustainable development model that balances economic and environmental performance, achieving ecological improvement alongside high-quality socioeconomic development [22,23]. However, its implementation is often constrained by multiple factors, including scarce green resources, high risks, and lengthy transition cycles [24]. The resource-based view offers a critical perspective here. This theory posits that a firm's competitive advantage and strategic breakthroughs stem from its possession of heterogeneous strategic resources [25]. As a disruptive general-purpose technology, artificial intelligence is increasingly becoming an emerging strategic resource for manufacturing enterprises to address challenges and build differentiated advantages.

AI contributes to green transformation by enabling firms to build heterogeneous green resources. Specifically, using big data processing and knowledge graph technologies, AI helps break down internal and external information barriers related to green development. It transforms fragmented information—such as industry low-carbon standards and cutting-edge environmental technologies—into structured knowledge, alleviating inefficiencies in traditional knowledge acquisition [26]. Through real-time monitoring of production energy consumption and carbon emission accounting, AI can precisely identify resource wastage points, thereby enhancing the utilization efficiency of green resources [27]. By leveraging deep learning algorithms to simulate the entire process of green process improvements and environmental equipment R&D, AI may reduce innovation trial-and-error costs and potentially accelerates the commercialization of green technology outcomes, enabling manufacturing enterprises to develop differentiated advantages in green technology resource reserves. The above mechanisms suggest that AI possesses the technological potential to drive corporate green transformation. This inference is supported by recent empirical evidence that AI can facilitate firms' environmental transformation [28–30]. However, while existing studies have examined AI's effects on specific environmental outcomes, the direct effect of AI on green transformation has not been systematically tested. Examining this relationship is important for understanding whether AI's technological potential translates into tangible organizational change. Based on the above analysis, we propose:

Hypothesis 1. *Artificial intelligence positively impacts the green transformation of manufacturing enterprises.*

Based on the resource-based view, artificial intelligence provides unique strategic resources for corporate green transformation. However, resources themselves cannot automatically translate into competitive advantage; their value realization depends on the dynamic capabilities of enterprises to integrate, construct, and reconfigure these resources [15].

Green transformation is not merely a qualitative leap in knowledge and technology; it also involves capabilities such as information acquisition, data governance, industrial chain integration, and production model innovation. Enhancing an enterprise's endoge-

nous motivation for green transformation, to a certain extent, means elevating its own green dynamic capabilities [31]. Leveraging its robust perception, learning, and intelligent decision-making capabilities, artificial intelligence can holistically enhance a company's effectiveness in identifying opportunities, restructuring resources, and implementing change, thereby systematically strengthening its dynamic capabilities. As a high-level capability enabling enterprises to reconfigure internal and external resources for rapid adaptation to complex environments, dynamic capabilities have received extensive theoretical and empirical support for their role in promoting corporate green transformation [16,18]. They enable enterprises to effectively sense opportunities, flexibly adjust resources, and continuously drive green innovation. Based on this, the article proposes the following hypothesis:

Hypothesis 2. *Artificial intelligence drives green transformation in manufacturing enterprises by enhancing dynamic capabilities.*

To further reveal the underlying pathways of this mechanism, the article deconstructs dynamic capabilities into three core dimensions—absorptive capability, innovative capability, and adaptive capability—and analyzes how AI empowers these capabilities to drive manufacturing enterprises' green transformation.

2.1. Artificial Intelligence, Absorptive Capability, and Corporate Green Transformation

As discussed in the Introduction, absorptive capability refers to a firm's ability to acquire, assimilate, and apply new external knowledge. Prior studies have established that firms with stronger absorptive capabilities are better positioned to identify and internalize external technological opportunities, thereby enhancing their innovation performance [32,33]. In the context of green transformation, absorptive capability enables firms to scan, interpret, and integrate dispersed information on emerging environmental regulations, green technology trends, and market demands [34]. AI, in turn, can strengthen this capability. By automating the acquisition and processing of large-scale external information—through natural language processing and knowledge graph construction—AI transforms fragmented data into structured knowledge [35,36]. Recent studies further confirm that AI literacy significantly enhances green absorptive capacity [37], and that AI promotes green innovation by strengthening knowledge absorption capacity, with absorptive capacity serving as a key moderator in the AI–green innovation relationship [38]. This suggests that AI may enhance firms' absorptive capability and, through this mechanism, facilitate green transformation. Based on this, the article proposes the following hypothesis:

Hypothesis 2a. *Artificial intelligence drives green transformation in manufacturing enterprises by enhancing absorptive capacity.*

2.2. Artificial Intelligence, Innovation Capability, and Corporate Green Transformation

As discussed in the Introduction, innovative capability refers to a firm's ability to generate new products, processes, and business models in response to environmental changes [20]. Prior research has established that firms with stronger innovative capabilities are better positioned to adapt to changing market conditions and technological trajectories, thereby securing long-term competitive advantage [15,39]. In the context of green transformation, innovative capability enables firms to move beyond incremental improvements and develop novel solutions that deliver both environmental and economic benefits [40]. AI can strengthen this capability. By leveraging generative design and digital twin simulation, AI expands the boundaries of innovative possibilities, allowing firms to explore solutions that traditional R&D approaches may overlook [40,41]. AI-driven automation of routine

R&D tasks also frees up human capital for more creative problem-solving and exploration of green technological frontiers. Recent empirical evidence confirms that AI transformation significantly enhances enterprise innovation capability [42], that AI adoption significantly improves corporate green innovation capability [43], and that AI, as a “co-worker,” reshapes corporate culture and strengthens innovation capability [37]. This suggests that AI may enhance firms’ innovative capability and, through this mechanism, facilitate green transformation. Based on this, the article proposes the following hypothesis:

Hypothesis 2b. *Artificial intelligence drives the green transformation of manufacturing enterprises by stimulating innovation capabilities.*

2.3. Artificial Intelligence, Adaptive Capability, and Corporate Green Transformation

In the context of green transformation, this capability manifests as an enterprise’s ability to perceive, interpret, and respond effectively to dynamic factors such as stringent environmental regulations, fluctuations in green market demand, and low-carbonization pressures within supply chains. Traditional environmental adaptability models, relying on periodic reporting and experiential judgment, struggle to address increasingly volatile and stringent environmental regulations alongside rapidly evolving market preferences due to information lag, ambiguous interpretation, and delayed response. Artificial intelligence enables enterprises to build real-time, precise digital environmental perception and response systems [44]. On the one hand, leveraging IoT sensors and natural language processing technologies, AI achieves real-time, precise, and panoramic perception of internal operational data and external environmental signals. On the other hand, based on machine learning and predictive models, AI performs in-depth correlation analysis of multi-source data, enabling forward-looking assessments of future policies, market demands, and risk trends, thereby reducing environmental uncertainty and decision ambiguity [45]. Furthermore, leveraging intelligent decision optimization algorithms and digital twin systems, AI enables enterprises to dynamically adjust production parameters, supply chain strategies, and R&D directions, achieving optimized resource allocation and calibrated strategic responses.

The resulting advanced adaptive capability constitutes the operational mechanism ensuring effective implementation of green transition strategies. When enterprises can perceive external dynamics in real time, conduct forward-looking assessments, and dynamically calibrate internal operations, they gain the capability to promptly optimize energy consumption, adjust green product lines, and mitigate risks of misalignment between transition initiatives and external environmental changes. Thus, robust adaptive capability serves as the critical operational pivot for transforming strategic intent into sustainable green practices that co-evolve with the environment. Based on this, the article proposes the following hypothesis:

Hypothesis 2c. *Artificial intelligence drives green transformation in manufacturing enterprises by enhancing adaptability.*

2.4. Hypotheses on Heterogeneity

The enabling role of AI in manufacturing enterprises’ green transformation is significantly moderated by internal and external contextual factors. Regarding ownership structure, non-state-owned enterprises typically face intense market competition and resource constraints. Their flexible decision-making mechanisms and pronounced profit orientation create favorable conditions for leveraging AI to optimize production processes, reduce environmental costs, and build differentiated competitive advantages [8]. State-owned enterprises, however, bear multiple policy objectives and social responsibilities,

resulting in relatively weaker market-driven incentives for AI-enabled green transformation. At the enterprise scale level, large-scale enterprises possess more robust financial reserves and more comprehensive data infrastructure, enabling them to systematically advance the green deployment of AI in R&D, manufacturing, and management, achieving significant economies of scale [46]. In contrast, small- and medium-sized enterprises are often constrained by resource and capability bottlenecks, resulting in insufficient depth and sustainability of AI application, which may limit the effectiveness of their green transformation. At the industry-specific technology level, non-high-tech enterprises typically face stronger environmental regulatory pressures. AI provides them with technological support for cost reduction, efficiency improvement, and clean production, making its enabling effects more prominent. In contrast, high-tech industries rely more on continuous R&D accumulation for green innovation, where AI often plays a supporting role, potentially contributing less to their transformation. Based on this, the article proposes the following hypothesis:

Hypothesis 3. *The promotional effect of AI on the green transformation of manufacturing enterprises is more pronounced in non-state-owned enterprises, large-scale enterprises, and non-high-tech industries.*

Accordingly, the theoretical framework constructed in this paper is illustrated in Figure 1.

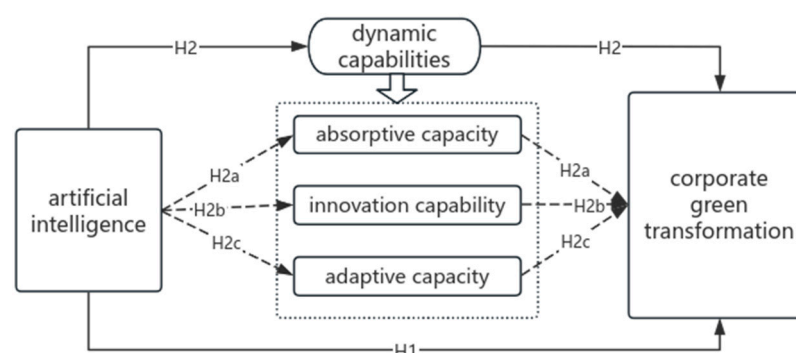


Figure 1. Theoretical analysis framework.

3. Research Design

3.1. Data Sources

To examine the impact of artificial intelligence on the green transformation of manufacturing enterprises and its underlying mechanisms, this study focuses on Chinese A-share-listed manufacturing companies from 2012 to 2023. Annual reports were sourced from the official websites of the Shanghai (<http://www.sse.com.cn>) and Shenzhen Stock Exchanges (<http://www.szse.cn>). Environmental protection-related data primarily originated from the China National Research Data Service Platform (CNRDS). Additional financial and corporate governance data were obtained from the CSMAR database and the WIND database. To ensure data reliability, the original sample underwent the following processing: (1) exclusion of firms labeled as ST, *ST, or PT during the study period; (2) removal of observations with severe missing values in core variables; (3) truncation of all continuous variables at the 1% level.

3.2. Variable Selection and Explanation

Explanatory Variable: Artificial Intelligence (AI). Drawing from Yao et al. (2024) [1], text analysis was employed for measurement. Specifically, the “Management Discussion

and Analysis" (MD&A) section of listed companies' annual reports served as the textual data foundation. This section centrally reflects corporate technology applications, strategic planning, and future development directions, offering authoritative and highly relevant information. A dedicated AI keyword dictionary was constructed, comprising 73 terms systematically selected to cover three major dimensions of AI technology—underlying technologies, core technologies, and general technologies—following the classification framework of Yao et al. (2024) [1]. This dictionary includes key terms such as "artificial intelligence," "knowledge graph," "data mining," and "intelligent supervision." Keyword identification and frequency counting were then conducted based on the dictionary. The natural logarithm of (total word frequency + 1) serves as the measurement indicator for corporate AI adoption. Higher values indicate deeper AI integration in strategic statements and business descriptions.

Prior empirical studies have validated the effectiveness of this text-based approach. Evidence shows that the frequency of technology-related keywords in annual reports is significantly and positively associated with firms' objective innovation outcomes [34,35], suggesting that textual attention to a given technology domain meaningfully reflects firms' actual technological efforts and resource allocation in that domain. Therefore, we adopt AI word frequency as our primary measure of adoption.

Dependent Variable: Corporate Green Transformation (GT). This paper employs text analysis to construct a multidimensional keyword dictionary, thereby developing a corporate green transformation index. The green transformation dictionary construction process is as follows: ① Preprocess annual reports obtained from authoritative platforms like the Shanghai and Shenzhen Stock Exchanges and Juchao Information Network, then perform word segmentation using the Jieba Chinese word segmentation tool. To enhance recognition accuracy in environmental domains, the study incorporated specialized dictionaries for green manufacturing, pollution control, and related terms into Jieba. ② Draw from national five-year plans, the Environmental Protection Law, the Technical Guidelines for Evaluating Corporate Environmental Behavior, the Green Manufacturing Standardization White Paper, and other policy documents, while referencing Li & Wang (2021) [47] and Xie & Zhu (2021) [48]. This identified core seed terms like "clean production," "circular economy," and "energy conservation and emission reduction," covering five dimensions: advocacy initiatives, strategic concepts, technological innovation, pollution control, and monitoring management. ③ Following mainstream practices, a preliminary keyword pool was formed, from which duplicates and terms unrelated to green transition were removed, ultimately creating a green transition lexicon comprising 113 keywords. ④ Python (version 3.14) tools were used to count keyword frequencies. The total word frequency was incremented by one and then taken to its natural logarithm to derive the corporate green transition index, measuring the emphasis and implementation orientation toward green development at the strategic text level. While this text-based approach involves inherent subjectivity, it captures firms' strategic orientation toward green development comprehensively and systematically across five dimensions, and has been validated in prior studies [22,23,48].

Control Variables: To control for other potential factors, the study incorporates the following firm-level control variables: firm size (Size), debt-to-equity ratio (Leverage), profitability (Roa), and growth potential (Growth). Firm size is included because larger firms have more resources for green investment and face greater stakeholder pressure. Leverage is controlled as highly leveraged firms face tighter financial constraints. Profitability captures firms' financial slack for green investment. Growth potential is included as high-growth firms may trade off environmental investment against market expansion. Other firm-level characteristics are either absorbed by firm fixed effects or considered less relevant based on the literature. The model also controls for year fixed effects and firm fixed

effects to mitigate omitted variable bias. Specific definitions and measurement methods for each variable are detailed in Table 1.

Table 1. Variable selection and measurement.

Variable Type	Variable Name	Symbol	Variable Measurement
Dependent variable	Corporate green transition	GT	Using text analysis to calculate the total frequency of green transition terms, add 1, and take the natural logarithm
Explanatory variables	Artificial intelligence	AI	The comprehensive indicator obtained from the article is incremented by 1, and then the natural logarithm is taken
	Dynamic capabilities	Dy	Absorptive capacity, innovative capacity, and adaptive capacity are standardized and then summed
Mediating variable	Absorptive capacity	Ab	R&D expenditure to operating revenue ratio
	Innovation capacity	In	Sum of standardized R&D intensity and technical personnel ratio
	Adaptability	Ad	Negative value of the ratio of the standard deviation to the mean for R&D expenditure, capital expenditure, and advertising expenditure
Control variables	Enterprise size	Size	Natural logarithm of total assets
	Return on assets	Roa	Net profit/total assets
	Debt-to-asset ratio	Lev	Total liabilities at end of period/total assets at end of period
	Enterprise growth capacity	Growth	Enterprise revenue growth rate

3.3. Model Specification

This paper utilizes panel data from Chinese listed manufacturing enterprises to examine the impact of artificial intelligence on the green transformation of manufacturing enterprises, constructing the following fixed-effects model:

$$GT_{it} = \alpha_0 + \alpha_1 AI_{it} + \alpha_2 Controls_{it} + \mu_t + \gamma_i + \varepsilon_{it} \quad (1)$$

Among these, i and t represent the firm and year, respectively. GT_{it} is the dependent variable, representing the green transition of manufacturing firms; AI_{it} is the core explanatory variable, representing artificial intelligence; $Controls_{it}$ is the set of control variables; μ_t and γ_i are the firm fixed effect and year fixed effect, respectively; ε_{it} is the random disturbance term. The model primarily focuses on the coefficient α_1 , whose sign and significance reflect the direction of influence between variables and statistical reliability.

4. Empirical Analysis

4.1. Descriptive Statistics

Table 2 presents descriptive statistics for all variables in the study. The table indicates that the mean green transformation score for manufacturing firms is 3.479, with a standard deviation of 0.866. The distribution spans from 0.000 to 5.497, suggesting that the sample firms' green transformation efforts are generally at a moderately high level, with significant variation across firms. This variation provides a necessary foundation for exploring influencing factors. The mean for artificial intelligence is 0.926, with a standard deviation of 1.188, spanning from 0.000 to 6.153. This reflects that while the sample as a whole possesses a certain foundation in AI, there are gaps in its penetration across different enterprises. This characteristic aligns with the current reality of uneven diffusion of artificial intelligence across industries in China. The mediating variables, including absorptive capability (Ab), innovative capability (In), and adaptive capability (Ad), also exhibit considerable variation across firms, with means of 0.040, 0.908, and -0.727 , respectively, and standard deviations of 0.097, 0.504, and 0.307, providing sufficient empirical foundation for examining their mediating roles.

Table 2. Descriptive statistics results.

Variable	Sample Size	Mean	Standard Deviation	Minimum	Maximum
GT	12,833	3.479	0.866	0.000	5.497
AI	12,833	0.926	1.188	0.000	6.153
Dy	12,830	0.000	2.024	−4.448	54.454
Ab	12,833	0.040	0.097	0.000	5.452
Ad	12,830	−0.727	0.307	−1.414	−0.012
In	12,833	0.908	0.504	−3.571	2.000
Size	12,833	21.969	1.842	0.000	26.452
Leverage	12,833	0.385	0.193	0.000	0.908
Roa	12,833	0.039	0.066	−0.556	0.222
Growth	12,833	0.158	0.380	−0.673	5.076

4.2. Correlation Analysis and Multicollinearity Diagnostics

Table 3 presents the results of the correlation analysis and multicollinearity diagnostics. The results show that AI is positively and significantly correlated with GT, with a correlation coefficient of 0.1248 ($p < 0.01$), providing preliminary support for the productivity-enhancing role of AI. The control variables generally correlate with GT in the expected directions; size is positively correlated with GT, while SOE is negatively correlated with GT.

Table 3. Correlation matrix and multicollinearity diagnostics.

Variable	GT	AI	Size	Leverage	Growth	Soe	VIF
GT	1.0000						
AI	0.1248 ***	1.0000					1.02
Size	0.0558 ***	0.0061	1.0000				1.19
Leverage	−0.0056	−0.0205 **	0.3867 ***	1.0000			1.23
Growth	0.0503 ***	−0.0009	0.0455 ***	0.0533 ***	1.0000		1.01
Soe	−0.0794 ***	−0.1336 ***	0.1703 ***	0.2512 ***	−0.0832 ***	1.0000	1.11
Mean VIF							1.11

Notes: Lower-left triangle reports Pearson correlation coefficients. *** $p < 0.01$, ** $p < 0.05$. The last column reports the variance inflation factor (VIF) for each independent variable. VIF values exceeding 10 are typically considered indicative of severe multicollinearity. The dependent variable GT is not included in the VIF calculation.

More importantly, the absolute values of the correlations among the independent variables are all well below the conventional threshold of 0.8, with the highest being 0.3867. This suggests that severe multicollinearity is unlikely to be a major concern.

To further validate this conclusion, we compute the VIF for each regressor. As shown in the last column of Table 3, the VIF values range from 1.01 to 1.23, with a mean of 1.11—all far below the rule-of-thumb threshold of 10. These results confirm that multicollinearity does not materially affect our subsequent regression estimates.

4.3. Baseline Regression

Table 4 presents the benchmark regression results for the impact of artificial intelligence (AI) on the green transformation (GT) of manufacturing enterprises. Column (1) shows the results without any control variables or fixed effects, where the coefficient is positively significant at the 1% level, preliminarily indicating a positive association between the two. After adding control variables in Column (2), the AI coefficient remains stable. Column (3), controlling for year fixed effects, shows a decline in the coefficient to a non-significant level, indicating that time trends are a significant confounding factor. Column (4), controlling simultaneously for firm and year, yields an AI coefficient of 0.0263, significant at the 1% level. This demonstrates that AI continues to significantly drive the

green transformation of manufacturing firms even after controlling for time and firm heterogeneity, validating Hypothesis 1. The economic magnitude of this effect is meaningful. A one-standard-deviation increase in AI adoption is associated with a 0.0263 increase in green transformation, representing about 0.8% of the sample mean (3.479). While this percentage may appear modest, green transformation is a gradual, long-term organizational process rather than a short-term response to technological changes. The persistence of the AI coefficient at the 1% significance level across all specifications confirms its substantive role as a driver rather than a marginal contributor to green transformation. The variation in control variable coefficients across columns reflects the sequential inclusion of fixed effects. When firm fixed effects are introduced in Column (4), time-invariant firm-specific heterogeneity is absorbed, which may alter the coefficients of control variables that are correlated with these fixed characteristics. Overall, the limited significance of the control variables suggests that the AI effect is not driven by observable firm characteristics, further reinforcing the robustness of our main findings.

Table 4. Benchmark regression results.

Variable	(1)	(2)	(3)	(4)
	GT	GT	GT	GT
AI	0.0910 *** (0.0065)	0.0906 *** (0.0065)	0.0051 (0.0044)	0.0263 *** (0.0087)
Size		0.0290 *** (0.0046)	0.0050 (0.0034)	0.0015 (0.0045)
Leverage		−0.1111 ** (0.0467)	0.0164 (0.0299)	−0.0086 (0.0544)
Roa		0.1739 (0.1317)	−0.0971 (0.0848)	−0.2476 ** (0.1125)
Growth		0.1041 *** (0.0204)	0.0101 (0.0131)	0.0014 (0.0144)
Controls	No	Yes	Yes	Yes
Year	No	No	Yes	Yes
Firm	No	No	No	Yes
N	12,833	12,833	12,833	12,833
R ²	0.0155	0.0215	0.5959	0.6081

Note: *** and ** denote significance levels of 1% and 5%, respectively; the values in parentheses represent the corresponding robust standard errors.

4.4. Robustness Tests

Lagged Variable Method: To mitigate potential reverse causality—where manufacturing firms with higher green transition levels may be more inclined to invest in AI—the study re-estimates using a lagged AI variable (one period behind). Column (1) of Table 5 shows the coefficient for lagged AI at 0.0204, significant at the 5% level, confirming the conclusion persists after accounting for lag effects.

Alternative Measure: The baseline AI adoption measure relies on textual word frequency from annual reports, which may raise concerns about whether “talking about AI” genuinely reflects “doing AI.” To directly address this concern, we construct an objective proxy based on AI-related invention patent applications ($\ln(1 + \text{patents})$) from the CNRDS database. This measure captures firms’ actual technological outputs rather than managerial discourse. Column (2) of Table 5 shows that the coefficient on AI patents is 0.1233, significant at the 1% level. The result is robust, confirming that the positive effect of AI on GT is not driven by the textual measurement approach but reflects substantive AI innovation activities.

Table 5. Robustness test results.

Variable	(1) One-Period Lag	(2) Alternative Measure	(3) Remove Outliers	(4) After 2015	(5) Add Control
AI			0.0223 *** (0.0086)	0.0285 *** (0.0105)	0.0264 *** (0.0087)
L.AI	0.0204 ** (0.0102)				
AI patent ownership		0.1233 *** (0.0181)			−0.0366 (0.0365)
Constant	2.4863 *** (0.1031)	2.0834 *** (0.1314)	2.4341 *** (0.0817)	2.5001 *** (0.1080)	2.3725 *** (0.0914)
Controls	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes
N	11,039	12,833	12,466	10,950	12,833
R2	0.6028	0.0162	0.5961	0.5652	0.6086

Note: Standard errors are shown in parentheses. Columns (1)–(5) present robust standard errors, while columns (6)–(7) present clustered standard errors. *** and **, denote significance levels of 1% and 5%, respectively.

Outlier Removal: To thoroughly eliminate potential interference from extreme values, the study removed observations at the top and bottom 1% percentiles for both the green transformation and AI variables of manufacturing firms. As shown in Column (3), the AI coefficient is 0.0223, significant at the 1% level, indicating robust results.

Sample Period Adjustment: The 2015 launch of national strategies like Made in China 2025 marked the initiation of systematic policy promotion for AI. To test robustness under this explicit policy environment, the sample was restricted to 2015–2023. Results in Column (4) show a positively significant AI coefficient, maintaining robust conclusions.

Control Variables Adjustment: To avoid omission bias, new control variables were incorporated into the baseline model. The AI coefficient remained at 0.0264 and was significant at the 1% level (Column 5). The coefficient of AI remains positively significant, further supporting the robustness of our findings.

5. Testing the Mechanism of Action

The theoretical analysis proposes that AI primarily drives green transformation by enhancing manufacturing firms' absorptive capacity, innovation capability, and adaptive capacity. Drawing on Jiang T (2022) [49], this study examines AI's impact on these three mediating pathways through the following econometric model:

$$M_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 Control_{it} + \mu_t + \gamma_i + \varepsilon_{it} \quad (2)$$

where i and t denote firm and year, respectively; M represents the mediating variables; and the remaining variables are set consistent with the baseline regression (1).

All mediating variables are measured following mainstream academic practices to ensure comparability and validity; Dynamic Capabilities (Dy) are comprehensively reflected by synthesizing measures of three sub-capabilities, adopting the theoretical framework proposed by Teece et al. (2007) [15]. Specifically: ① Absorptive Capacity (Ab) is measured by adapting the research of Yang et al. (2020) [50], measured by R&D intensity, where higher values indicate stronger capabilities in identifying and assimilating external knowledge; ② Innovation Capability (In), integrating the conceptual framework from Yang et al.

(2020) [50], is calculated by standardizing and summing two indicators, R&D investment intensity and the proportion of technical personnel, to comprehensively reflect internal innovation resources and potential; ③ Adaptive Capability (Ad): Drawing from Zhao et al. (2016) [51], this is measured using the negative value of the coefficient of variation for three types of expenditures: R&D, capital, and advertising. A higher value indicates greater flexibility in resource allocation and stronger environmental adaptive capability. Ultimately, the composite dynamic capability index is obtained by summing the standardized values of these three sub-capability indicators.

The results of the mediation analysis are presented in Table 6. Column (1) shows that the regression coefficient for AI is 0.200, significant at the 1% level, indicating that AI significantly enhances corporate dynamic capability. As a comprehensive higher-order capability, dynamic capability is systematically strengthened through AI-enabled empowerment, thereby reinforcing the overall potential for enterprises to continuously adapt and evolve within complex dynamic environments. These findings confirm AI's significant driving effect on dynamic capabilities, while the theoretical mechanism of dynamic capabilities facilitating green transformation is supported by the existing literature. Thus, the pathway through which AI drives green transformation in manufacturing enterprises by enhancing dynamic capabilities is established, validating Hypothesis 2.

Table 6. Mediating effect analysis results.

Variable	(1)	(2)	(3)	(4)
	Dy	Ab	In	Ad
AI	0.1995 *** (0.0156)	0.0052 *** (0.0011)	0.0175 * (0.0106)	0.0128 *** (0.0049)
Constant	−2.3149 *** (0.7152)	0.0190 *** (0.0060)	0.3880 *** (0.0830)	−0.9740 *** (0.0440)
Controls	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
N	12,833	12,833	12,833	12,830
R ²	0.3330	0.1660	0.1280	0.3530

Note: *** and * denote significance levels of 1% and 10%, respectively; the values in parentheses represent the corresponding robust standard errors.

Column (2) results show that the coefficient for AI's effect on absorptive capability is 0.005, significant at the 1% statistical level, indicating that AI significantly enhances manufacturing enterprises' knowledge absorption capabilities. As a key dynamic capability, absorptive capacity, when strengthened by AI, effectively promotes the deep integration of internal knowledge bases with external green technology frontiers. This, in turn, significantly improves the accuracy of identifying and efficiency of evaluating green transformation opportunities, providing a crucial knowledge foundation and cognitive prerequisite for transitioning toward green development. These findings support the pathway of AI driving green transformation by enhancing absorptive capability, validating Hypothesis 2a.

Column (3) results show that the coefficient for AI's impact on innovation capability is 0.018, statistically significant at the 10% level. This indicates that AI effectively stimulates innovation capability in manufacturing enterprises. As a dynamic capability enabling enterprises to transform concepts into new products or processes, innovation capability—when further empowered by AI—can optimize R&D pathways through intelligent algorithms and implement green reengineering of traditional production processes. This shortens the cycle from developing green innovations to commercializing them. These findings sup-

port the pathway of AI driving green transformation by stimulating innovation capability, thereby validating Hypothesis 2b.

Column (4) shows that the coefficient for AI's impact on adaptive capability is 0.012, statistically significant at the 1% level, indicating that AI effectively enhances manufacturing enterprises' adaptive capability. Adaptive capability, as the dynamic capacity of manufacturing enterprises to respond to external environmental changes, adjust strategies, and reconfigure resources, enables companies to respond more agilely to environmental regulations and market fluctuations after AI empowerment. This allows for dynamic optimization of resource allocation and action plans. Enhanced adaptive capability ensures enterprises maintain strategic resilience and continuously refine their transformation pathways amid the uncertainties of green transition. These findings support the pathway through which AI drives green transformation by enhancing adaptive capability, validating Hypothesis 2c.

6. Heterogeneity Analysis

(1) Analysis of Heterogeneity in Property Rights Nature

Given the systemic differences in development strategies, resource acquisition, and operational objectives between state-owned and non-state-owned enterprises, this study distinguishes between the two to examine the property rights heterogeneity in AI's impact on the green transformation of manufacturing enterprises. Results in Table 7, columns (1) and (2), indicate that AI's promotional effect is more pronounced and significant in non-state-owned enterprises. This may stem from systemic differences in goal orientation, incentive mechanisms, and environmental contexts between the two enterprise types. Non-state-owned enterprises typically face stronger market competition pressures. Their application of AI is often directly driven by efficiency gains and cost reduction, aligning closely with the economic benefits of green transformation. Consequently, they possess stronger mechanisms to deeply integrate AI into green innovation practices. In contrast, state-owned enterprises often bear multiple objectives, have relatively complex decision-making processes, and exhibit a tendency to avoid innovation risks. These factors may weaken the efficiency of converting AI into green outcomes, resulting in a less significant impact of AI on green transformation in state-owned manufacturing enterprises.

(2) Analysis of Heterogeneity in Enterprise Scale

This study further distinguishes between large-scale enterprises and small-to-medium-sized enterprises to examine the heterogeneity of AI's impact on manufacturing firms' green transformation across scale dimensions. The regression results in columns (2) and (4) show that the AI coefficient is 0.0439 and statistically significant at the 1% level for large-scale enterprises, whereas it fails to pass the significance test for small-scale enterprises. This divergence likely stems from asymmetries in resource endowments and capability structures between the two types of enterprises. Large enterprises typically possess more robust financial reserves, more sophisticated digital infrastructure, and more specialized R&D teams. This enables them to better sustain the continuous investment required for AI technology, thereby more effectively translating technological advantages into green process improvements or product innovations. Conversely, while small-scale enterprises benefit from flexible organizational structures and rapid responsiveness, they are often constrained by financing limitations and weak technological accumulation. This results in higher risks and costs when advancing the deep integration of AI and green transformation, preventing the full manifestation of technology-enabled effects.

(3) Analysis of Industry-Specific Technological Heterogeneity

Given structural differences in technological opportunities and innovation ecosystems across industries, this study categorizes the sample into high-tech and traditional sectors to examine the industry-specific heterogeneity of AI's impact on manufacturing enterprises' green transformation. The regression results in columns (5) and (6) of Table 7 indicate that AI's promotional effect is statistically significant at the 5% level across industries with different technological attributes. The AI coefficient in high-tech industries is 0.0203, while in non-high-tech industries, this coefficient reaches 0.0545, significantly higher than the former. This disparity reflects the differentiated logic of AI's marginal gains and catch-up effects in empowering green transformation across different industrial contexts. In high-tech industries, enterprises possess robust R&D capabilities and accumulated green technologies. AI primarily functions as an accelerator for efficiency gains and path optimization, yielding relatively limited marginal benefits. In non-high-tech industries, however, enterprises often face more urgent green transition pressures and more pronounced technological capability gaps. AI not only optimizes existing processes but also has the opportunity to uncover energy-saving and consumption-reduction pathways through data-driven insights—pathways that traditional experience struggles to identify—or achieve breakthroughs at the process level through intelligent means. This results in a more pronounced catch-up effect.

In summary, AI's catalytic effect on manufacturing enterprises' green transformation is more pronounced in non-state-owned enterprises, large-scale enterprises, and non-high-tech industries, validating Hypothesis 3.

Table 7. Heterogeneity analysis results.

Variable	(1) State-Owned Enterprise	(2) Non-State-Owned Enterprises	(3) Large-Scale	(4) Small-Scale	(5) High-Tech	(6) Non-High-Tech
AI	0.0304 (0.0201)	0.0265 *** (0.0098)	0.0439 *** (0.0137)	0.0121 (0.0128)	0.0203 ** (0.0095)	0.0545 ** (0.0239)
Constant	2.1863 *** (0.1569)	2.5217 *** (0.1205)	2.5983 *** (0.1368)	2.3282 *** (0.1033)	2.3075 *** (0.0877)	2.4277 *** (0.1664)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes	Yes
N	3353	9480	6416	6417	10,635	2198
R ²	0.6151	0.6047	0.5921	0.6086	0.6069	0.6172

Note: *** and ** denote significance levels of 1% and 5%, respectively; the values in parentheses represent the corresponding robust standard errors.

7. Conclusions and Policy Implications

7.1. Conclusions

How artificial intelligence empowers corporate green transformation is a key issue for understanding the essence and pathways of green development in new-quality productive forces. Based on panel data from manufacturing enterprises from 2012 to 2023, this study systematically examines the impact and mechanisms of artificial intelligence on the green transformation of China's manufacturing enterprises. The main findings are as follows: (1) Artificial intelligence can significantly enhance the green transformation level of manufacturing enterprises, and this conclusion remains valid after a series of robustness tests. This extends prior work on AI's environmental effects [10,38] by confirming its impact at the organizational level rather than on isolated outcomes such as green patents or emission reductions. (2) AI influences the green transformation process by enhancing enterprises' three dimensions of dynamic capabilities: absorption capability, innovation capability, and adaptation capability. Specifically, absorption capacity facilitates knowledge acquisition

and internalization; innovation capacity drives technology conversion and output; and adaptation capacity enables dynamic adjustment and risk buffering. This advances prior research on individual mediating mechanisms [7,8] by testing three parallel pathways within a unified framework. (3) Heterogeneity analysis indicates that AI's impact is more pronounced in non-state-owned enterprises, large-scale enterprises, and non-high-tech enterprises. This suggests that AI's green enabling effects are not universally beneficial technological dividends; their efficacy is systematically modulated by firm resource endowments, institutional environments, and industry attributes. This aligns with evidence on differential AI effects across firm types [27] and clarifies the boundary conditions under which AI most effectively drives green transformation. Based on these findings, the paper proposes the following policy recommendations.

Lowering the systemic barriers to green AI applications is essential. Given the robust positive effect of AI on green transformation identified in this study, lowering these barriers is a critical policy priority. Currently, many enterprises—particularly small- and medium-sized enterprises—continue to face common challenges, including high algorithm costs, difficulties in data acquisition, and lengthy technical validation cycles. Governmental efforts should focus on lowering the systemic barriers to green AI applications through the establishment of green computing infrastructure and carbon data monitoring networks for manufacturing enterprises, as well as through the provision of inclusive computing subsidies and standardized data interfaces. A special program should be established for “AI + Green Manufacturing” technology validation and pilot projects, designed to provide cost-sharing for initial expenses and risk mitigation for enterprises undertaking their first AI-driven green process upgrades.

A dynamic capability support system should be built. Since the mechanism analysis shows that absorptive, innovative, and adaptive capabilities serve as the key mediating pathways. An industry-level knowledge platform for green AI applications and a common technology map should be developed, and a repository of best practices and roadmaps for AI-enabled green transformation should be regularly published in order to lower the cognitive barriers for enterprises regarding the identification, access, and understanding of cutting-edge technologies. A green R&D funding mechanism oriented toward actual emission reduction performance should be established, with ex-post rewards and tax credits provided to relevant enterprises. Digital twin simulation platforms and transformation risk-sharing funds should be promoted to provide enterprises with a low-cost, low-risk environment for trial and error. An “AI + Green” pilot error-tolerance mechanism should be established, allowing enterprises to conduct technical debugging and strategic adjustments within a controlled scope, thereby strengthening their dynamic resilience when responding to technological iterations and policy fluctuations.

Implement differentiated industrial guidance strategies. Since the heterogeneity analysis shows that AI's effect is stronger in non-state-owned, large-scale, and non-high-tech firms, a “one-size-fits-all” approach is inappropriate. For non-state-owned enterprises, prioritize optimizing their institutional environment to ensure equitable access to green credit and specialized subsidies while lowering transition barriers through shared technology platforms and lightweight solutions. For large enterprises with established first-mover advantages, incentivize them to lead as chain anchors by setting green supply chain standards, opening technical scenarios, and exporting solutions to drive coordinated transformation across the industrial chain—particularly for SMEs. Additionally, strategically guide AI-driven green technologies toward non-high-tech traditional industries with complex processes and emission-intensive operations. Establish industry-specific common technology challenge lists and adopt competitive “bounty-style” funding models to achieve breakthroughs and empower the entire chain.

7.2. Limitation and Future Research

Several limitations of this study should be acknowledged. First, the measurement of AI adoption relies on word frequency in annual reports, which captures firms' stated rather than actual AI implementation. To address this concern, we have conducted robustness checks using AI patent and intangible asset indicators. Nevertheless, future research could refine the measurement using more granular data, such as AI-related capital expenditure or detailed technology adoption surveys. Second, although this study validates the mediating role of dynamic capabilities, it does not dynamically track their evolution and iteration processes. Future studies could employ case studies or multi-period tracking data to examine the interactive sequences and dominant mechanisms of each dynamic capability dimension across different transformation stages, further unraveling the black box of capability construction.

Author Contributions: Conceptualization, Y.W. and M.J.; methodology, M.J.; software, S.L.; validation, Y.W., M.J. and S.L.; formal analysis, M.J.; investigation, Y.W.; resources, Y.W.; data curation, M.J.; writing—original draft preparation, Y.W.; writing—review and editing, M.J.; visualization, S.L.; supervision, Y.W.; project administration, Y.W.; funding acquisition, Y.W. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the Key Project of Shanxi Provincial Philosophy and Social Sciences [Grant No. 2025ZD108], and the Key Projects of Shanxi Provincial Federation of Social Sciences [Grant Nos. SSKLZDKT2025140, SSKLZDKT2025143].

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Acknowledgments: The authors thank the editors and anonymous reviewers for their constructive comments on earlier versions of this paper.

Conflicts of Interest: The authors declare no conflicts of interest.

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