How AI Application Empowers Corporate Green Transformation

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ABSTRACT Amid escalating climate pressures and China's "dual carbon" commitments, the green transition of enterprises is constrained by two intertwined challenges: deficient data governance and persistent technological hurdles. This study exploits the staggered rollout of National AI Innovation Application Pilot Zones as a quasi-natural experiment. Drawing on panel data covering A-share listed firms in China from 2009 to 2022, and applying a staggered Difference-in-Differences framework, we estimate the causal effect of Artificial Intelligence adoption on corporate green transition and identify the mechanisms driving this relationship. The study confirms that AI application, leveraging its powerful data insight and decision optimization capabilities, effectively resolves the conflict between economic benefits and environmental performance, significantly facilitating corporate green transformation. Mechanism analysis reveals that AI mainly plays an empowering role through four pathways: first, alleviating information asymmetry in investment and financing, thereby expanding corporate financing cash flow; second, aligning with national macro-strategies to enhance the ability to obtain government subsidies; third, promoting labor skill upgrading to strengthen core human capital; and fourth, reshaping data generation mechanisms to improve the quality of environmental information disclosure. Heterogeneity analysis shows that this promoting effect is more pronounced in technology-intensive, high-tech, and highly competitive industries; meanwhile, non-state-owned enterprises and enterprises in the growth and maturity stages benefit more. Accordingly, this paper recommends continuously deepening pilot zone construction, promoting the integration of "AI + Green Finance," precisely allocating fiscal subsidies, accelerating the cultivation of interdisciplinary talent, and implementing differentiated policy guidance strategies.

INDEX TERMS AI Application; Corporate Green Transformation; Innovation Application Pilot Zones

I. INTRODUCTION

The World Meteorological Organization (WMO) reported that the global average temperature in 2024 was 1.55°C higher than pre-industrial levels, further highlighting the severity of the climate crisis. In this context, advancing carbon emission reduction and achieving carbon neutrality have become universal consensus and collective actions of the international community. As climate change effects deepen and sustainability gains traction, green transition has emerged as an imperative for corporate viability and growth. Under the traditional extensive growth model, the contradiction between resource consumption and environmental pollution continues to escalate, compounded by the gradual implementation of global green trade rules such as carbon tariffs. Enterprises not only face increasing environmental compliance pressure but also urgently need to enhance the actual effectiveness of their transformation. Meanwhile, the continuous advancement of China's "dual carbon" goals and the issuance of policies such as the "Guiding Opinions on Accelerating the Green Development of Manufacturing" have clarified the path of synergistic transformation through "digital technology + green low-carbon," pointing the direction for enterprises to break through transformation bottlenecks.

Currently, enterprises face two major practical bottlenecks in promoting green transformation: first, weak data governance capabilities, where energy consumption and carbon emission data suffer from complex sources, difficult collection, and low accuracy, making it hard to support precise decision-making; second, systematic obstacles to breakthroughs in key green technologies, particularly bottlenecks in core materials and processes, leading to high application costs and limited energy efficiency improvements. The rapid development of AI application technology provides a new path to address these challenges. Relying on its powerful data integration and intelligent analysis capabilities, AI application can efficiently process complex energy and carbon emission data, providing a reliable data foundation for decision optimization. Meanwhile, through machine learning methods, AI can accelerate the R&D process of new materials and processes, effectively shortening the technology breakthrough cycle. Furthermore, in specific application scenarios such as smart grids and intelligent buildings, AI promotes rapid knowledge accumulation and continuous system optimization through real-time monitoring and dynamic regulation, thereby improving technology maturity and providing critical iteration and validation space for green low-carbon technologies to move from the experimental stage to large-scale application.

As an important carrier for the deep integration of AI application and the real economy, the construction of National AI Innovation Application Pilot Zones has significant practical meaning. From Shanghai Pudong New Area to Nanjing, Wuhan, Changsha, and other pilot zones established nationwide, the layout has gradually expanded, with functional positioning focusing on "planning reform, promoting application, and guiding experience." By integrating multi-dimensional resources such as computing infrastructure, policy support, and industrial ecosystems, these zones are becoming key supports for driving corporate green transformation. Unlike scattered applications of single technologies, pilot zones build a complete ecosystem of "computing support–scenario empowerment–policy guarantee," transforming AI's technical advantages into systematic change momentum–covering dynamic energy consumption regulation in production, low-carbon collaborative scheduling in supply chains, and carbon footprint tracing throughout the product life cycle–thereby providing enterprises with full-chain, intelligent green transformation solutions.

The deep integration of AI application and corporate green transformation essentially achieves efficient docking between technological innovation and industrial demand. The intelligent computing power, advanced algorithms, and diversified application scenarios gathered in pilot zones can effectively address practical pain points such as data fragmentation, insufficient efficiency, and high costs during corporate transformation, driving green transformation from "passive compliance" to "active efficiency improvement." Against the background of the Fourth Industrial Revolution reshaping the global competitive landscape with AI application at its core, the following two key questions urgently need in-depth exploration: First, can AI application effectively drive corporate green transformation? Second, through what specific mechanism pathways does it achieve this impact? This study exploits the staggered rollout of National AI Innovation Application Pilot Zones (hereinafter, the Pilot Zone Policy) as a quasi-natural experiment. Drawing on panel data of Chinese listed firms spanning 2009–2022, and applying a staggered Difference-in-Differences framework, we estimate the causal effect of this policy on corporate green transition and identify the mechanisms through which it operates.

II. THEORETICAL ANALYSIS AND HYPOTHESIS DEVELOPMENT

Why has AI application become a key force in promoting corporate green transformation? The fundamental reason is that it effectively resolves the long-standing dilemma between economic benefits and environmental performance under the traditional development model. Under the traditional paradigm, environmental investment is often viewed as an additional cost burden for enterprises. However, AI application, leveraging its powerful data insight, predictive optimization, and automated decision-making capabilities, profoundly reconstructs the efficiency attributes and value logic of green transformation. It not only transforms green from a compliance cost into an efficiency engine and innovation source that can create value but also achieves synergistic progress between corporate competitiveness improvement and ecological environmental protection at the micro level. First, AI achieves refined efficiency improvements, reducing resource consumption and waste generation from the source. In the core operational links of enterprises, whether in manufacturing, energy management, or supply chain collaboration, AI can achieve dynamic optimization based on real-time analysis of multi-dimensional data. Additionally, predictive maintenance based on equipment operation data not only avoids production interruptions and resource waste caused by sudden failures but also indirectly reduces environmental pressure from resource extraction and waste disposal by extending equipment life cycles. Second, AI possesses unique capabilities in optimizing complex systems, achieving global optimality through dynamic collaboration. Modern enterprise production and energy systems are increasingly complex, and traditional manual management and automated control struggle to cope with dynamic coordination problems under multi-objective, multi-constraint conditions. AI can find optimal process solutions that balance product quality, energy efficiency levels, and emission constraints among massive parameter combinations, achieving greening of the production process. Third, AI innovates corporate environmental management and strategic decision-making paradigms in a data-driven manner. Green transformation depends on precise quantification and full-process tracking of environmental performance such as carbon emissions, and AI's data processing capabilities make this goal achievable. Meanwhile, in major investment decisions, AI can comprehensively evaluate environmental risks, policy trends, and economic benefits, providing corporate managers with more comprehensive and rigorous decision-making basis for green strategic choices. Based on this, this paper proposes the following hypothesis:

Hypothesis 1: AI application can facilitate corporate green transformation.

The core reason why AI application can increase financing cash flow during corporate green transformation lies in effectively alleviating two structural problems that have long existed in the green investment and financing field: "information asymmetry" and "difficult risk pricing." By reshaping the interaction mechanism between fund suppliers and demanders, AI systematically improves the external financing environment for enterprises from three dimensions: cost, channels, and value. First, AI enhances financial intermediaries' ability to "identify green," reducing debt financing costs and financing constraints for green transformation enterprises. Under the traditional credit model, financial institutions lack effective quantitative assessment methods to accurately identify enterprises' true green attributes and transformation effectiveness. The resulting information barriers often lead to pricing distortions and resource misallocation in green credit. AI application enables banks to integrate and deeply mine multi-dimensional data such as energy consumption and emissions from enterprise production and operations, conducting more precise dynamic assessments of enterprises' green performance and transformation potential. Second, AI application has spawned new financial products and financing models, opening diversified incremental funding channels for enterprises. Based on AI's carbon accounting and dynamic risk assessment capabilities, financial institutions can design innovative credit products deeply tied to green performance. Such models transform enterprises' carbon emission data into visual credit assets, enabling green performance to be directly converted into financing advantages. Third, from the perspective of enterprises' own capabilities, AI application inherently improves their green innovation performance and carbon emission reduction capabilities. This directly strengthens enterprises' market competitiveness and long-term development resilience, while also equipping them with stronger attractiveness when facing increasingly strict ESG investment standards. Based on this, this paper proposes the following hypothesis:

Hypothesis 2: AI application can facilitate corporate green transformation by increasing corporate financing cash flow.

The reason why AI application can enhance enterprises' likelihood of obtaining government subsidies stems from the systematic alignment formed in strategic orientation and information transmission, thereby effectively enhancing the government's willingness and basis for fiscal support. On one hand, AI application aligns enterprises' development paths with national macro-strategic orientations, thereby obtaining preferential policy resources. Under the top-level design of promoting manufacturing toward high-end, intelligent, and green transformation, enterprises' active introduction of AI technology essentially represents the concrete practice of national strategy at the micro level. This directional alignment makes enterprises key targets for identification and support by governments at all levels. In other words, the "going with the trend" demonstrated by enterprises through technological upgrades constitutes a strategic prerequisite for obtaining policy support. On the other hand, AI application plays a key role in alleviating information asymmetry between government and enterprises, thereby reducing the government's screening costs and identification difficulties. When allocating subsidy resources, governments often face the dilemma of difficulty in discerning enterprises' true transformation intentions and capabilities. The introduction and deployment of AI technology, as a high-cost, high-complexity investment behavior, sends a credible signal to the outside world that the enterprise is committed to long-term development and deep transformation. This signaling effect helps enhance the government's cognitive trust in the enterprise, making it more likely to be regarded as a high-quality entity with development potential, thereby receiving priority consideration in policy resource allocation. Based on this, this paper proposes the following hypothesis:

Hypothesis 3: AI application can facilitate corporate green transformation by enhancing enterprises' ability to obtain government subsidies.

In the process of AI-driven corporate green transition, human capital upgrading serves as a pivotal micro-level mechanism. At its core, AI does not merely substitute for labor but catalyzes systematic advances in workforce knowledge, skills, and competencies, thereby furnishing essential impetus for green transformation. First, through knowledge spillover effects and intelligent skill training, AI accelerates the diffusion and iteration of green knowledge and skills within organizations, effectively improving the speed and adaptability of human capital renewal to better respond to the inherent requirements of rapid skill iteration demanded by green transformation. Second, AI application promotes the structural upgrading of labor from repetitive, procedural tasks to high-value-added, creative work. In the green transformation process, large amounts of tedious data processing work such as carbon emission accounting, environmental performance monitoring, and waste classification can be efficiently completed by AI systems. This liberates employees from low-value-added repetitive labor, allowing them to devote more energy to tasks requiring complex judgment, innovative thinking, and strategic decision-making. Finally, AI application has spawned interdisciplinary talent possessing both green literacy and digital skills, promoting the optimization and reconstruction of human capital structure. Human-machine collaborative work environments promote the evolution of traditional positions toward intelligence, thereby deriving emerging positions such as AI energy management, carbon data analysis, and intelligent environmental protection equipment operation and maintenance. To adapt to these changes, employees must actively learn cross-disciplinary knowledge, being familiar with business logic, mastering AI tool applications, and possessing environmental compliance awareness. This skill reconstruction process directly reflects the appreciation of human capital. Based on this, this paper proposes the following hypothesis:

Hypothesis 4: AI application can facilitate corporate green transformation by strengthening human capital.

The improvement of corporate information disclosure quality by AI application stems from its systematic reshaping of information generation and dissemination mechanisms, manifesting a composite effect of "internal and external cultivation." On one hand, from the perspective of internal corporate governance, AI's deep embedding in information production processes significantly enhances the "hard power" of information disclosure. Specifically, based on automated data collection and real-time monitoring technology, AI can penetrate underlying business systems such as corporate finance, production, and environmental performance, achieving continuous tracking and automated verification of core indicators, effectively avoiding data lags and errors caused by manual reporting in traditional models. Meanwhile, intelligent verification tools can quickly identify and prompt data inconsistencies, format flaws, and other superficial errors during document preparation, thereby improving the rigor and standardization of disclosure texts. Furthermore, AI's complex modeling and quantitative analysis capabilities can support enterprises in conducting climate risk stress tests, emission peak predictions, and energy consumption structure optimization. The resulting forward-looking and substantive disclosure information can also enhance the information content and decision usefulness of environmental reports. On the other hand, from the perspective of external corporate supervision, the introduction of AI also strengthens behavioral constraints on market entities, forming a "soft environment" for improving information disclosure quality. The improvement of information granularity and data traceability makes corporate disclosure content more verifiable. Investors, regulators, and the public can use intelligent analysis tools to cross-check and verify the authenticity of information, thereby increasing the difficulty and risk of enterprises engaging in "greenwashing" or selective disclosure. Meanwhile, AI application helps alleviate corporate financing constraints and optimize resource allocation, weakening their motivation to obtain short-term benefits through false environmental propaganda. The increased media attention and analytical tracking also amplify external supervision pressure, prompting enterprises to disclose authentic and complete environmental information. Based on this, this paper proposes the following hypothesis:

Hypothesis 5: AI application can facilitate corporate green transformation by improving the quality of corporate information disclosure.

III. RESEARCH DESIGN

A. ECONOMETRIC MODEL SPECIFICATION

Building on the preceding theoretical framework, this study exploits the Pilot Zone Policy as a quasi-natural experiment and applies a Difference-in-Differences (DID) approach to estimate its causal effect on corporate green transition. The empirical specification is as follows:

$$GT_{i,t} = \alpha_0 + \alpha_1 did_{i,t} + \alpha_2 Control_{i,t} + \mu_i^1 + r_j^1 + \lambda_t^1 + \varepsilon_{i,t}^1. \tag{1}$$

In the above equation, i and t represent the firm and year, respectively. The dependent variable $GT_{i,t}$ represents the green transformation of firm i in year t. The core explanatory variable $did_{i,t}$ is a dummy variable indicating whether firm i implemented the Pilot Zone Policy in year t. If firm i implemented the Pilot Zone Policy in year t and in subsequent years, did takes the value of 1, and 0 otherwise. $Control_{i,t}$ represents a series of control variables affecting corporate green transformation. α, β, and γ are parameters to be estimated. μ_i, η_j, and λ_t represent firm fixed effects, industry fixed effects, and year fixed effects, respectively. $\varepsilon_{i,t}$ represents the random disturbance term. This paper constructs the following econometric model to examine the mechanism pathways through which AI application affects corporate green transformation:

$$\begin{aligned} Mechanism_{i,t} = \gamma_0 + \gamma_1 did_{i,t} + \gamma_2 Control_{i,t} \\ + \mu_i^2 + r_j^2 + \lambda_t^2 + \varepsilon_{i,t}^2. \end{aligned} \tag{2}$$

In the above equation, $Mechanism_{i,t}$ is the mechanism variable through which AI application affects corporate green transformation. The meanings of the remaining variables are consistent with Equation (1).

B. DEPENDENT VARIABLE

From a technical perspective, the core of corporate green transformation lies in substantive changes in production technology and processes. As an important quantitative carrier of technological innovation, patents can effectively characterize enterprises' actual input and output in the green technology field, thus becoming a key indicator for measuring green innovation activities. According to the "International Patent Classification Green List" published by the World Intellectual Property Organization (WIPO), researchers can clearly classify corporate patents into green patents and non-green patents based on a unified classification framework, thereby identifying their technological innovation behaviors in the environmental protection field. Compared with patent grant data, patent application data is not affected by time lags caused by examination cycles and can more timely reflect enterprises' current technological innovation intentions and strategic layouts, thus being widely regarded as a leading indicator for measuring corporate green transformation. Based on this, following the research method of Li Wenjing and Zheng Manni (2016), this paper adopts the natural logarithm of the number of green patent applications as the proxy variable for corporate green transformation.

C. CORE EXPLANATORY VARIABLE

The core explanatory variable in this paper is the national-level Pilot Zone Policy. Based on the first to third batches of national pilot zone lists issued by the Ministry of Industry and Information Technology in 2019, 2021, and 2022, respectively, and following the research design of Yu Shaolong and Shi Hong (2025), this paper constructs the interaction term of the policy dummy variable ($Treat_i$) and the policy implementation time dummy variable ($Time_t$), denoted as did_{it}, to characterize whether firm i was covered by the

Pilot Zone Policy in year t. Specifically, for firms in the sample that were approved as pilot zones, the value is set to 1 from the year of approval and in subsequent years, and 0 otherwise.

TABLE 1. List of National AI Innovation Application Pilot Zones

Batch	Approval Year	Pilot Cities
First	May-19	Shanghai (Pudong New Area)
	Oct-19	Jinan-Qingdao, Shenzhen
Second	Feb-21	Beijing, Tianjin (Binhai New Area), Hangzhou, Guangzhou, Chengdu
Third	Sep-22	Nanjing, Wuhan, Changsha

D. CONTROL VARIABLES

To mitigate omitted-variable bias, this study draws on the practices of Cai Qingfeng et al. (2024), Jiang Zhongyu and Wu Fuxiang (2024), and Chu Peipei and Zhang Rao (2025), incorporating a set of control variables to account for other potential determinants of corporate green transition. The selection and measurement of these variables are detailed below: Firm Age (Age), computed as the number of years since the firm's listing date; Ownership Concentration (Big1), measured by the shareholding proportion of the largest shareholder; Book-to-Market Ratio (BM), defined as the ratio of total owners' equity to market value; Management Expense Intensity (Mfee), calculated as management expenses divided by operating revenue; Operating Cash Flow Ratio (Cashflow), measured by net operating cash flow scaled by total assets; Leverage Ratio (Lev), computed as total liabilities divided by total assets; Return on Assets (ROA), defined as net profit over total assets; and Board Size (Board), measured by the natural logarithm of the number of directors.

E. MECHANISM VARIABLES

(1) Financing Cash Flow (CFF). This paper measures the financing cash flow level by the proportion of total equity and debt financing to total assets.

(2) Government Subsidies (Sub). To accurately identify government support directly related to corporate R&D activities, this paper focuses on government R&D investment funds to measure the intensity of government subsidies obtained by enterprises.

(3) Human Capital (Human). This paper characterizes the human capital level by the proportion of R&D personnel to total employees.

(4) Social Responsibility Information Quality (Sriq). Drawing on 12 key indicators from the "Basic Information Table of Listed Companies' Social Responsibility Reports," this study constructs a composite index to gauge the quality of corporate social responsibility disclosure, employing standardization and weighted aggregation across the selected indicators.

F. DATA DESCRIPTION

This study examines A-share listed firms on the Shanghai and Shenzhen stock exchanges from 2009 to 2022. The initial sample is screened according to the following criteria to ensure data quality and mitigate the influence of anomalous observations: (1) financial sector firms are excluded; (2) firms designated as ST, *ST, or PT in the current year are excluded; (3) firms with a leverage ratio exceeding or equal to 1 are excluded; (4) observations from the IPO year and prior are excluded; (5) firms with missing values for key variables are excluded; (6) for sporadic missing data, linear interpolation is applied. Additional firm-level financial data are drawn from the CSMAR database. Following these procedures, the final unbalanced panel comprises 37,578 firm-year observations from 4,344 listed companies. Table 2 presents the descriptive statistics for each variable.

TABLE 2. Descriptive Statistics of Variables

Variable Type	Variable Name	Variable Description	Observations	Mean	Std. Dev.	Minimum/Maximum
Dependent Variable	GT	Corporate Green Transformation	37,578	0.2602	0.612	0 / 3.1354
Explanatory Variable	did	AI Application	37,578	0.118	0.3226	0 / 1
Control Variables	Age	Firm Age	37,578	9.7149	7.6451	0 / 28
	Big1	Ownership Concentration	37,578	34.5074	14.9289	8.575 / 74.5657
	BM	Book-to-Market Ratio	37,578	0.9907	1.1044	0.0926 / 6.848
	Mfee	Management Expense Ratio	37,578	0.086	0.0664	0.0083 / 0.4043
	Cashflow	Cash Flow Ratio	37,578	0.0483	0.069	-0.1576 / 0.246
	ROA	Return on Total Assets	37,578	0.0443	0.063	-0.2082 / 0.2264
	Board	Board Size	37,578	9.2717	2.2446	5 / 17
	CFF	Financing Cash Flow	37,578	0.5984	2.1488	0.0009 / 71.2649
	Sriq	Information Disclosure Quality	37,578	0.4327	0.2659	0 / 1
	Litinum	Litigation Risk	37,578	0.0775	0.3146	0 / 5.5759
	Innova	R&D Intensity	37,578	0.0034	0.0438	0 / 0.2418
Mechanism Variables	CFF	Financing Cash Flow	37,578	0.5984	2.1488	0.0009 / 71.2649
	Sub	Government Subsidies	37,578	0.0345	0.5432	0 / 0.5432
	Human	Human Capital	37,578	10.3159	13.6931	0 / 100
	Sriq	Information Disclosure Quality	37,578	0.4327	0.2659	0 / 1

IV. EMPIRICAL ANALYSIS

A. BENCHMARK REGRESSION RESULTS

Before estimating the benchmark model, we first conducted panel unit root tests on each variable and found that all variables are stationary series. Additionally, we conducted correlation coefficient tests and variance inflation factor tests on each explanatory variable and found that correlation coefficients are all less than 0.7 and variance inflation factors are all less than 10, indicating that there is no obvious multicollinearity among variables. Table 3 presents baseline regression estimates of AI adoption on corporate green transition. Column (1) reports estimates without controls; columns (2)–(5) progressively add control variables, firm fixed effects, industry fixed effects, and year fixed effects. To address potential within-industry and temporal correlation in disturbances, column (2) clusters standard errors at the firm level. Columns (3)–(5) cluster standard errors at the firm-year, firm-industry, and year-industry dimensions, respectively. Across all specifications, AI adoption exerts a statistically significant positive effect on corporate green transition.

TABLE 3. Benchmark Regression Results

Variable	(1)	(2)	(3)	(4)	(5)
did	0.0648***	0.0598***	0.0598***	0.0598***	0.0598***
	-0.0152	-0.0152	-0.0111	-0.0156	-0.0125
Control Variables	No	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Clustered at Firm Level	Yes	Yes	No	No	No
Clustered at Firm-Year Level	No	No	Yes	No	No
Clustered at Firm-Industry Level	No	No	No	Yes	No
Clustered at Year-Industry Level	No	No	No	No	Yes
R^2	0.6378	0.6394	0.6394	0.6394	0.6394
Observations	37,142	37,142	37,142	37,142	37,142

Note: ***, *, * indicate significance at the 1%, 5%, and 10% levels, respectively. Values in parentheses below coefficients are cluster-robust standard errors. The same applies to subsequent tables.

This paper takes column (2) as the benchmark result for analysis. The results show that AI application can significantly facilitate corporate green transformation at the 1% significance level, thereby preliminarily verifying that Hypothesis 1 is established. Specifically, holding other conditions constant, compared with enterprises that have not implemented AI application, AI application can promote an average increase of 0.0598 units in corporate green transformation.

B. PRE-ASSUMPTION EVALUATION

1) Parallel Trend Assumption Assessment and Dynamic Effect Analysis

According to Angrist and Pischke (2009), the parallel trends assumption between treated and control groups is a critical prerequisite for ensuring the validity of Difference-in-Differences estimates when evaluating the Pilot Zone Policy's effect on corporate green transition. Specifically, absent policy shocks, firms subject to and exempt from the policy should exhibit identical time-series trajectories in green transition outcomes. Accordingly, following Wu Chaopeng and Yan Zehao (2023), this study employs an event-study approach for pre-trend testing, with the policy implementation year serving as the reference period. The empirical specification is as follows:

$$GT_{i,t} = \phi_0 + \sum_{k=-5}^{3+} \beta_k did_{i,t_0+k} + \phi_1 Control_{i,t} + \mu_i^4 + r_j^4 + \lambda_t^4 + \varepsilon_{i,t}^4. \tag{3}$$

In Equation (3), did_{i,t_0+k} represents the dummy variable for the k-th year of enterprises implementing the Pilot Zone Policy. k denotes the temporal distance from Pilot Zone Policy implementation, where k=0 marks the implementation year. Pre-treatment periods are coded as k=-1, -2, -3, -4, -5, with k≤-5 representing five or more years prior to implementation. Post-treatment periods are coded as k=1, 2, 3+, with k≥3 capturing three or more years following implementation. Other variables follow the definitions in Equation (1). The parameter of central interest is β_k, which captures the differential in corporate green transition between treated and untreated firms in year k. If β_k is statistically indistinguishable from zero for k<0, the pre-treatment coefficients exhibit a relatively flat trajectory, consistent with the parallel trends assumption. Conversely, if β_k displays a significant upward or downward trend for k<0, this would indicate pre-existing divergence between treatment and control groups, violating the identifying assumption. To visualize these estimates, Figure 1 plots the coefficient trajectory, with the horizontal axis denoting years relative to policy implementation and the vertical axis representing the magnitude of the estimated coefficients.

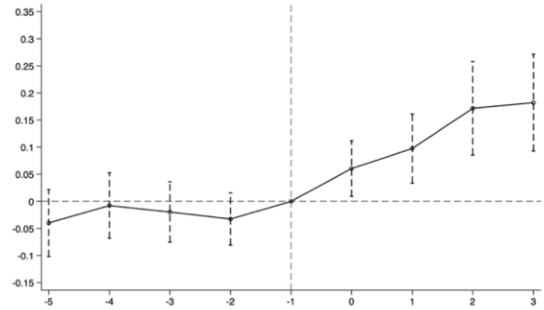

FIGURE 1. Parallel Trend Assumption Assessment

As shown in Figure 1, for pre-treatment periods (k<0), the estimated coefficients of the Pilot Zone Policy on corporate green transition are generally statistically insignificant, indicating that prior to implementation, no systematic divergence existed in the trajectories of green transition between treated and control firms, thereby supporting the parallel trends assumption. For post-treatment periods (k>0), the coefficients exhibit a pronounced upward trajectory, suggesting that the Pilot Zone Policy accelerates corporate green transition and corroborating the robustness of the baseline estimates.

2) Placebo Test

To assess whether the estimated effect of the Pilot Zone Policy on corporate green transition is driven by random or unobservable factors, this study conducts a placebo test by randomly assigning pseudo-treatment status to firms, preserving the number of treated units corresponding to each policy rollout year, and re-estimating the treatment effect. This procedure is repeated 1,000 times. As shown in Figure 2, the resulting coefficient distribution approximates normality and is concentrated around zero. The benchmark estimate of 0.0133, indicated by the vertical dashed line, lies entirely outside this distribution, suggesting that the policy effect does not arise from random or unobservable confounders, thereby corroborating the robustness of the baseline findings.

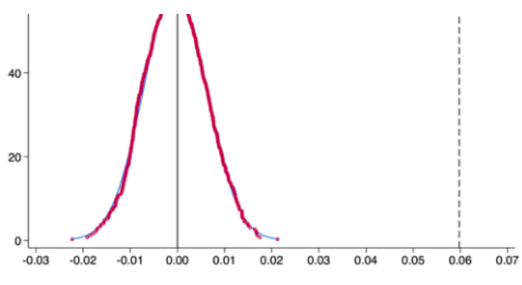

FIGURE 2. Placebo Test

C. ROBUSTNESS TESTS

1) Heterogeneous Treatment Effects Test

In the staggered DID model, the bad control group problem caused by samples receiving treatment at different time points may lead to potential bias in the multi-period DID estimator (Goodman-Bacon, 2021). Therefore, following Goodman-Bacon (2021), this paper first draws a treatment time distribution graph and conducts negative weight diagnosis and homogeneous treatment effect tests to preliminarily determine whether staggered DID has negative weight and heterogeneous treatment effect problems.

(1) Treatment Time Distribution Graph.

In staggered DID, individuals receiving policy treatment earlier may become the control group for individuals receiving treatment later, and the estimation coefficient of each period is affected by cross-period contamination (Borusyak and Jaravel, 2024), thereby interfering with the robustness of estimation results. To more intuitively judge the distribution of earlier-treated groups, later-treated groups, and never-treated groups in the sample, thereby preliminarily assessing the severity of heterogeneous treatment effects, this paper draws the treatment time distribution graph of AI application. As shown in Figure 3, during the sample period, cities not subject to policy intervention totaled 221, accounting for approximately 77.82% of the total sample, while cities receiving policy treatment are mainly concentrated in the later period of the sample, and there are no cities that always received treatment. The above results indicate that the treatment effect of AI application on corporate green transformation is less disturbed by bad control groups, and the estimation bias caused by heterogeneous treatment effects is small, thereby preliminarily verifying that the research results of this paper are robust.

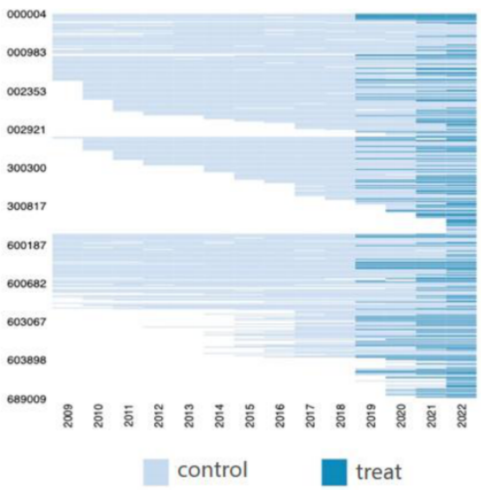

FIGURE 3. Treatment Time Distribution Graph

(2) Negative Weight Diagnosis.

Heterogeneous treatment effects across treated units or treatment periods are a primary source of negative weighting problems, which can induce substantial bias in the Two-Way Fixed Effects (TWFE) estimator (De Chaisemartin et al., 2020). Accordingly, following De Chaisemartin et al. (2020), this study constructs a residualized treatment variable. Given that this variable and its associated weights are proportional in magnitude and aligned in direction, the distribution of the residualized treatment variable reveals the size and sign of the weights. As shown in Figure 4, the proportion of residualized treatment variables exceeding zero in the treated group is 100%, with no negative weights detected. This indicates that all treated observations receive positive weights, thereby precluding bias in the TWFE estimator and corroborating the robustness of the empirical findings.

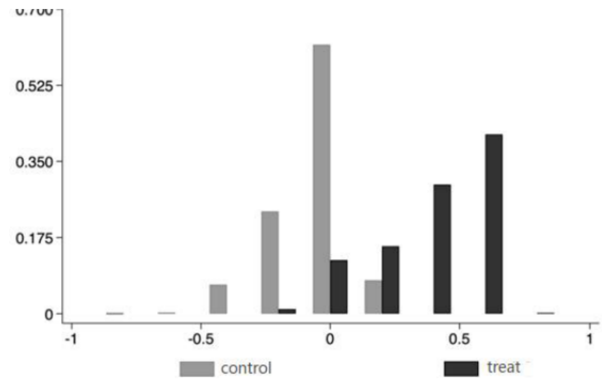

FIGURE 4. Residualized Treatment Variable Distribution Graph

(3) Homogeneous Treatment Effect Test

The homogeneous treatment effect assumption is an important prerequisite for testing whether the staggered DID estimator is credible. As Jakiela (2021) mentioned, homogeneous treatment effects will not affect estimation results due to negative weight problems in the treatment group sample, while heterogeneous treatment effects may still lead to biased estimation results even when positive weights exist in the treatment group sample. Therefore, following Jakiela (2021), this study constructs a residualized outcome variable and examines whether the correlation between the residualized outcome and the residualized treatment variable differs systematically between treated and control groups. As shown in Figure 5, the fitted lines for the two groups do not exhibit pronounced divergence, indicating that the slopes are statistically indistinguishable between Pilot Zone and non-Pilot Zone firms. This supports the homogeneous treatment effects assumption and corroborates the robustness of the empirical findings.

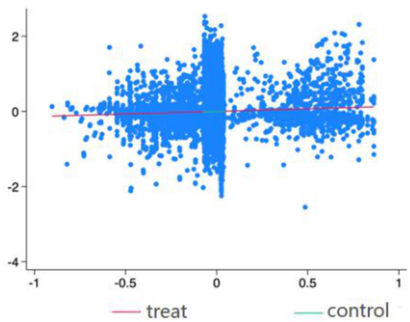

FIGURE 5. Homogeneous Treatment Effect Test

2) Heterogeneity-Robust Estimator Test

Although the treatment time distribution graph indicates that the policy treatment effect of the Pilot Zone Policy causes relatively small bias, it only preliminarily shows that the staggered DID estimator based on the TWFE framework will not cause large bias, and the robustness of the conclusion needs further testing. Since individuals receiving policy treatment earlier may become the control group for individuals receiving treatment later, leading to cross-period interference in the estimation coefficient of each period. Therefore, this paper still needs to pay attention to this issue. Referring to existing research, this paper respectively calculates the cohort-period average treatment effect and the imputation estimator to address the heterogeneous treatment effect problem.

(1) Calculating Cohort-Period Average Treatment Effects. To reduce estimation bias caused by heterogeneous treatment effects, Sun and Abraham (2021) set the control group as samples that “never received treatment” and “have not yet received treatment,” and use linear regression methods to calculate the average treatment effect within each cohort-period, then perform weighted averaging from the cohort and period dimensions to obtain the average treatment effect. As shown in Figure 6, after adopting the method of calculating cohort-period average treatment effects, the impact of AI application on corporate green transformation shows policy effects three periods after implementation due to policy transmission lag, and is significantly positive, proving that the benchmark conclusion of this paper remains robust.

(2) Imputation Estimator. Borusyak et al. (2024) proposed estimating the counterfactual outcome variable for each treated individual in each period from control group samples, thereby avoiding the “bad control group” problem. As shown in Figure 6, after adopting the imputation estimator method, the impact of AI application on corporate green transformation shows policy effects three periods after implementation due to policy transmission lag, and is significantly positive, proving that the benchmark conclusion of this paper remains robust.

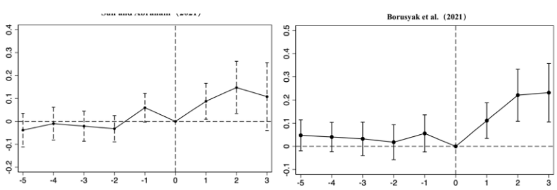

FIGURE 6. Heterogeneity-Robust Estimators

In summary, both results indicate that treatment effects are homogeneous, meaning that the weight of individuals receiving policy treatment earlier becoming the control group for individuals receiving treatment later in the sample does not significantly affect the policy effect. Meanwhile, AI application has a significant facilitating effect on corporate green transformation development, thereby proving that the benchmark conclusion of this paper remains robust.

V. MECHANISM ANALYSIS

According to the research hypotheses, AI application may facilitate corporate green transformation through financing constraints, government subsidies, human capital, and information disclosure quality. Table 4 reports the test results for the above hypotheses.

TABLE 4. Transmission Mechanism Analysis

Variable	(1) CFF	(2) Sub	(3) Human	(4) Sriq
did	0.118***	0.00382*	0.849***	0.0110**
	-0.0357	-0.002	-0.2434	-0.0055
Control Variables	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R^2	0.9035	0.7138	0.7943	0.651
Observations	37,142	37,142	37,142	37,142

The estimation results in column (1) of Table 4 indicate that the impact of AI application on financing cash flow is significantly positive, indicating that AI application can facilitate corporate green transformation by expanding financing cash flow. The core reason why AI application can increase financing cash flow during corporate green transformation lies in effectively alleviating two structural problems that have long existed in the green investment and financing field: “information asymmetry” and “difficult risk pricing.” By reshaping the interaction mechanism between fund suppliers and demanders, AI systematically improves the external financing environment for enterprises from three dimensions: cost, channels, and value. This verifies the establishment of Hypothesis 2. The estimation results in column (2) of Table 4 indicate that the impact of AI application on government subsidies is significantly positive, indicating that AI application can facilitate corporate green transformation through government subsidies. The reason why AI application can enhance enterprises’ likelihood of obtaining government subsidies stems from the systematic alignment formed in strategic orientation and information transmission, thereby effectively enhancing the government’s willingness and basis for fiscal support. On one hand, AI application aligns enterprises’ development paths with national macro-strategic orientations, thereby obtaining preferential policy resources. On the other hand, AI application plays a key role in alleviating information asymmetry between government and enterprises, thereby reducing the government’s screening costs and identification difficulties. This verifies the establishment of Hypothesis 3. The estimates in column (3) of Table 4 reveal that AI adoption exerts a statistically significant positive effect on human capital, suggesting that firms enhance green transition by upgrading workforce quality. Human capital accumulation serves as a pivotal micro-level channel through which AI drives corporate green transition: rather than merely displacing labor, AI catalyzes systematic advances in employee knowledge, competencies, and skill sets, thereby furnishing essential impetus for green transformation. These findings confirm Hypothesis 4. The estimates in column (4) of Table 4 reveal that AI adoption exerts a statistically significant positive effect on information disclosure quality, suggesting that firms advance green transition by enhancing transparency. AI reshapes information generation and dissemination through a dual mechanism of "internal cultivation and external oversight." Internally, the deep integration of AI into information production processes substantially bolsters the technical capacity for disclosure. Externally, AI deployment strengthens behavioral constraints on market participants, fostering an institutional environment conducive to higher disclosure standards. These findings confirm Hypothesis 5.

VI. HETEROGENEITY ANALYSIS

A. HETEROGENEITY ANALYSIS BY INDUSTRY CHARACTERISTICS

First, factor endowments, R&D intensity, and payback horizons differ systematically across labor-intensive, capital-intensive, and technology-intensive sectors, potentially generating heterogeneous effects of AI adoption on corporate green transition. Accordingly, following Lei Guosheng and Yang Yang (2024), this study partitions the sample into capital-intensive (Capital), technology-intensive (Tech), and labor-intensive (Labour) industries, constructs corresponding dummy variables, interacts each with AI adoption, and incorporates these terms into Equation (1) to estimate sectoral disparities. The results are reported in column (1) of Table 5. Second, high-tech and non-high-tech industries show significant differences in improving resource allocation, which may lead to differentiated effects of AI application on corporate green transformation. In view of this, following the practice of Gu Xiaming et al. (2018), this paper divides the research sample into high-tech industry enterprises (Htech) and non-high-tech industry enterprises (Ltech), constructs two groups of dummy variables, interacts them with AI application, and incorporates them into Equation (1) for parameter estimation, thereby examining the differences in the impact of AI application on corporate green transformation between high-tech and non-high-tech industry enterprises. The corresponding estimation results are shown in column (2) of Table 5. Finally, competitive intensity shapes investment behavior and innovation efficiency differentially across sectors, which may yield heterogeneous effects of AI adoption on corporate green transition. Accordingly, following Yin Hongying and Li Chuang (2022), this study stratifies the sample into high-competition (Hcompet) and low-competition (Lcompet) industries, generates corresponding dummy variables, interacts each with AI adoption, and incorporates these interaction terms into Equation (1) to estimate cross-sector disparities. The results are presented in column (3) of Table 5.

TABLE 5. Heterogeneity Analysis by Industry Characteristics

Variable	(1)	(2)	(3)
did×Tech	0.122***		-0.0218
did×Capital	-0.0546**		-0.0232
did×Labor	0.0317		-0.0258
did×Htech		0.101***	-0.0233
did×Ltech		0.0215	-0.0175
did×Hcompet			0.0841***
did×Lcompet			0.0314*
Control Variables	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
R^2	0.64	0.64	0.64
Observations	37,142	37,142	37,142

The estimation results in column (1) of Table 5 indicate that the estimated coefficients of AI application on corporate green transformation for technology-intensive industry enterprises are significantly positive, for capital-intensive industry enterprises are significantly positive, while for labor-intensive industry enterprises this estimated coefficient is not significant. It can be seen that the impact of AI application on corporate green transformation is more prominent in technology-intensive industries. The estimation results in column (2) indicate that the estimated coefficient of AI application on corporate green transformation for high-tech industry enterprises is significantly positive, while for non-high-tech industry enterprises this estimated coefficient is not significant. It can be seen that the impact of AI application on corporate green transformation is more prominent in high-tech industries. The estimation results in column (3) indicate that the estimated coefficients of AI application on corporate green transformation for both high-competition and low-competition industry enterprises are significantly positive, with the former's coefficient value being larger than the latter. It can be seen that the impact of AI application on corporate green transformation is more prominent in high-competition industries.

B. HETEROGENEITY ANALYSIS BY ENTERPRISE CHARACTERISTICS

First, state-owned and non-state-owned enterprises show significant differences in the intensity of social responsibility undertaken when implementing national major development strategies, which may lead to differentiated effects of AI application on corporate green transformation. In view of this, following the practice of Wu Chaopeng and Yan Zehao (2023), this paper divides the research sample into state-owned enterprises (Soe) and non-state-owned enterprises (NoSoe), constructs two groups of dummy variables, interacts them with AI application, and incorporates them into Equation (1) for parameter estimation, thereby examining the impact of AI application on green transformation of state-owned and non-state-owned enterprises. The corresponding estimation results are shown in column (1) of

Table 6. Second, enterprises at different life cycles show significant differences in management strategies, resource allocation, and external support, which may lead to differentiated effects of AI application on corporate green transformation. In view of this, following the practice of Dickinson (2011), this paper divides the research sample into growth period (Growth), maturity period (Maturity), and decline period (Decline), constructs three groups of dummy variables, interacts them with AI application, and incorporates them into Equation (1) for parameter estimation, thereby examining the impact of AI application on green transformation of growth period, maturity period, and decline period enterprises. The estimation results are shown in column (2) of Table 6.

TABLE 6. Heterogeneity Analysis by Enterprise Characteristics

Variable	(1)	(2)
did×Soe	0.0281*	-0.0166
did×NoSoe	0.116***	-0.0272
did×Growth		0.0935***
did×Maturity		0.0538***
did×Decline		0.0223
Control Variables	Yes	Yes
Firm FE	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
R^2	0.64	0.64
Observations	37,142	37,142

The estimation results in column (1) of Table 6 indicate that the estimated coefficients of AI application on corporate green transformation for both non-state-owned and state-owned enterprises are significantly positive, but the former's coefficient value is larger than the latter. It can be seen that the impact of AI application on corporate green transformation is more prominent in non-state-owned enterprises. The estimation results in column (2) indicate that the estimated coefficients of AI application on corporate green transformation for both growth period and maturity period enterprises are significantly positive, with the former's coefficient value being larger than the latter, while for decline period enterprises this estimated coefficient is not significant. It can be seen that the impact of AI application on corporate green transformation is more prominent in growth period enterprises.

VII. CONCLUSIONS AND POLICY IMPLICATIONS

This study exploits the staggered rollout of the National AI Innovation Application Pilot Zone Policy as a quasi-natural experiment. Drawing on panel data of A-share listed firms on the Shanghai and Shenzhen stock exchanges spanning 2009–2022, and applying a staggered Difference-in-Differences framework, we systematically estimate the causal effect, transmission channels, and heterogeneous patterns of AI adoption on corporate green transition. The principal findings are as follows. First, AI adoption exerts a statistically significant positive effect on corporate green transition. Second, mechanism analysis reveals four primary channels: augmenting financing cash flows, enhancing access to government subsidies, upgrading human capital, and improving information disclosure quality. Third, heterogeneous effects are pronounced across industry and firm characteristics. By industry type, technology-intensive, high-tech, and high-competition sectors experience more pronounced benefits. By firm ownership and life-cycle stage, non-state-owned enterprises and firms in growth or maturity phases exhibit stronger green transition responses to AI adoption than state-owned enterprises and those in decline.

Based on the above conclusions, this paper proposes the following policy implications. First, continue to deepen the construction of National AI Innovation Application Pilot Zones, strengthening the foundational support for AI empowerment of green transformation. The layout scope of pilot zones should be further expanded, promoting the collaborative development of computing infrastructure, algorithm toolchains, and industry knowledge bases, and building a full-chain technology empowerment system covering "data collection–intelligent analysis–decision optimization." Meanwhile, encourage pilot zones to explore differentiated application scenario opening mechanisms, guide AI technology to deeply embed in key links of green transformation such as energy management, production manufacturing, and supply chain collaboration, and form replicable and promotable benchmark cases. Second, improve the institutional design for the integrated development of green finance and AI, smoothing financing channels for corporate green transformation. Support financial institutions in developing innovative credit products tied to green performance based on AI technology, promoting the transformation of energy consumption and emission data into "credit assets." Explore the establishment of AI-empowered green project evaluation and risk pricing platforms, reducing the degree of information asymmetry in green investment and financing, and guiding more social capital toward the green transformation field. Third, strengthen the precision and effectiveness of government subsidies guided by AI application. In the process of fiscal resource allocation, comprehensive consideration should be given to enterprises' actual investment in AI technology application and transformation effectiveness, constructing a subsidy screening mechanism based on multi-dimensional data dynamic monitoring. Meanwhile, encourage local governments to incorporate AI application into the support scope of special policies such as green manufacturing and energy conservation and emission reduction, forming policy synergy. Fourth, pay attention to the collaborative development of AI and human capital, cultivating interdisciplinary talent needed for green transformation. Support enterprises in conducting skill training and position restructuring under human-machine collaboration scenarios, promoting the transformation of employees from repetitive labor to high-value-added, creative work. Encourage universities and vocational colleges to set up interdisciplinary majors combining AI and green low-carbon, accelerating the cultivation of interdisciplinary talent possessing both digital literacy and green literacy. Fifth, establish and improve norms and standard systems for AI-empowered information disclosure. Promote enterprises to build AI-based carbon emission accounting and environmental performance monitoring systems, improving the granularity, real-time performance, and verifiability of information disclosure. Strengthen regulatory authorities' intelligent identification and of "greenwashing" behaviors, and create an open, transparent, authentic, and credible market environment. Sixth, implement differentiated and precise policy guidance strategies. Formulate classified support measures according to the characteristics of different industry types, ownership structures, and life cycle stages. For technology-intensive, high-tech industries and non-state-owned enterprises, further relax market access and increase R&D incentives. For growth period and maturity period enterprises, focus on supporting them in carrying out AI and green technology fusion application demonstrations. For decline period enterprises and labor-intensive industries, help them achieve smooth transition through technological transformation subsidies and transformation guidance.

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