



A Study on the Threshold of Organizational Complexity for Artificial Intelligence-Enabling Green Transformation in heavily Polluted Manufacturing Industries Under the TOE Framework

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Abstract. As the core driving force behind industrial transformation, artificial intelligence serves as a critical pillar for advancing the green and intelligent development of heavily polluting manufacturing sectors. Based on data from A-share heavily polluting manufacturing firms over the period 2009–2024, this paper examines the mechanism through which artificial intelligence affects the green transformation of heavily polluting manufacturing industries. The study finds that AI can promote green transformation by optimizing the labor force structure and attracting patient capital. Moreover, once organizational complexity reaches a certain threshold, this effect can be effectively unleashed. This study provides policy implications for promoting the differentiated advancement of intelligent and green development in the manufacturing industry.

Keywords: Artificial Intelligence, Green Transformation, Heavy-Polluting Manufacturing Industries, Threshold Effect

1 Introduction

As the world's largest carbon emitter, China's carbon emission activities have exerted tremendous pressure on ecosystems. Both the "dual carbon" goals mentioned at the United Nations General Assembly and the series of policy documents issued by the government emphasize the need to strengthen the supporting role of new technological paradigms in the green transformation (Shabur, 2024). In 2025, the State Council issued the "Opinions on Deeply Implementing the 'Artificial Intelligence+' Initiative," creating new opportunities to effectively reduce pollution emissions in the manufacturing sector. In light of this, this paper systematically examines the impact mechanism of artificial intelligence on the green transformation of heavily polluting manufacturing industries within the framework of the TOE theory, aiming to fill the research gap at the micro-enterprise level.

2 Literature Review and Research Gaps

In the study of drivers of green transformation, a large body of research has shown that stringent environmental regulations and effective policy incentives can significantly improve the green total factor productivity of heavily polluting manufacturing industries (Mahmood et al., 2022). On the other hand, internal governance is also considered an important factor affecting green transformation performance. Studies indicate that factors such as the shareholding ratio of institutional investors and long-term performance incentives for management (Hu & Hong, 2023) influence the green transformation decisions of heavily polluting manufacturing firms. Meanwhile, existing research on the relationship between AI and green transformation exhibits multifaceted characteristics. On the one hand, some scholars believe that AI, when fully integrated into industrial chains, enhances regional green transformation performance by improving energy efficiency and optimizing production processes (Shabur, 2024). On the other hand, AI may also induce scale expansion effects, thereby creating new environmental pressures (Qu & She, 2025). Furthermore, Babina et al. (2024) point out that the application of AI needs to cross a certain threshold before its promoting effect on green governance performance becomes evident. Thus, no consensus has yet been reached on the green transformation effect of artificial intelligence.

Overall, the existing literature has two main shortcomings. First, few studies have examined the green transformation of heavily polluting manufacturing industries from the perspective of AI as a technological driver, and there is a lack of an integrated theoretical framework. Second, no consensus has been reached on the impact of AI on the green transformation performance of heavily polluting industries. In light of this, this paper systematically investigates the internal mechanism through which AI enables the green transformation of heavily polluting manufacturing industries, using a sample of A-share listed firms in China from 2009 to 2024, and employing TOE framework and threshold effect models.

The marginal contributions of this paper are threefold. First, by introducing the TOE framework, provides an integrated analytical framework for the green transformation of heavily polluting manufacturing industries. Second, we incorporate a threshold regression model based on organizational complexity, revealing the “organizational unlocking condition” for AI-enabled green transformations. Third, the findings of this study provide direct empirical evidence for formulating targeted policy recommendations.

3 Theoretical Analysis and Research Hypotheses

This article examines the mechanisms by which AI empowers the green transformation of heavily polluting manufacturing industries, based on the three dimensions of TOE.

3.1 The Technological Dimension: The Direct Effects of Artificial Intelligence

Drawing on Schumpeter's theory of creative destruction (Caballero, 2008), AI not only systematically reconfigures the prevailing paradigm of production factors, thereby enabling heavily polluting manufacturing industries to break free from path dependence on high energy consumption and emissions at the source, but also delivers value through a fundamental restructuring of firms' resource endowments and strategic boundaries. On one hand, AI embedded into production processes through intelligent identification, real-time monitoring, and algorithmic optimisation enhances firms' energy efficiency and curbs resource waste; at the same time, AI shifts corporate decision-making from experience-driven to data-driven paradigms, fostering green technological innovation and emissions reduction. On the other hand, the application of AI enables heavily polluting manufacturing industries to develop dynamic competitive advantages rooted in data capabilities, algorithmic proficiency, and system integration. In this process, the green transformation of heavily polluting manufacturing evolves from a passive response to an imperative for enhancing long-term competitiveness. Accordingly, this study proposes the following hypothesis:

H1: Artificial intelligence exerts a positive driving effect on the green transformation of heavily polluting manufacturing industries.

3.2 The Organizational Dimension: The Indirect Effects of Labor Force Structure

Compared with conventional technologies, AI exhibits greater complexity, and its effective application depends critically on firms' organizational learning capabilities. Drawing on the resource-based view (Barney, 1991) and dynamic capabilities theory (Teece et al., 1997), a firm's sustained competitive advantage derives from its ability to integrate scarce strategic resources. Human capital is a paradigmatic example of such scarce strategic resources. As AI becomes embedded in production and management processes, it can substitute for low-skill tasks while simultaneously increasing demand for high-skill roles. In this process, firms' labor force structures gradually upgrade toward higher educational attainment. This upgrading not only provides intellectual resource support for green innovation activities but also, through the agglomeration of highly educated talent, helps break down information barriers across departments and facilitates the diffusion of innovation outcomes along industrial supply chains, thereby enabling firms to better align technological capabilities with green development goals. Accordingly, this study proposes the following hypothesis:

H2a: Artificial intelligence can promote the green transformation of heavily polluting manufacturing industries by optimizing firms' labor force structure.

3.3 The Environmental Dimension: The Mediating Effect of Patient Capital

AI-driven green transformations are typically characterised by large investment scales, long payback periods, and high return risks. Consequently, whether the green effects

materialise hinges on access to sustained, stable long-term capital support. Most traditional capital providers prioritize immediate returns, making it difficult to maintain continuous momentum for transformation. In contrast, patient capital can alleviate some of the pressure associated with unsuccessful innovation efforts, thereby easing financing constraints. The introduction of AI can enhance firms' long-term development prospects, thereby attracting patient capital. On one hand, AI improves firms' resource allocation efficiency and green innovation capabilities, signalling positive prospects to capital markets. On the other hand, AI-enhanced information processing and data governance capabilities also help increase capital market recognition of firms' long-term green development strategies. In this context, firms can more readily obtain long-term capital support and continuously channel such funds into areas such as energy conservation, emission reduction, and cleaner production, thereby further strengthening the green transformation outcomes. Accordingly, this study proposes the following hypothesis:

H2b: Artificial intelligence can promote the green transformation of heavily polluting manufacturing industries by attracting patient capital.

3.4 The Threshold Effect of Organizational Complexity

The enabling effect of AI on the green transformation of heavily polluting manufacturing industries is contingent upon contextual conditions. Among these, the organizational (O) dimension—particularly resource integration, managerial coordination, and technology absorptive capacity—largely determines whether AI can successfully drive such a transformation, because the effectiveness of AI adoption hinges critically on whether an organization internally fosters a sense of collaborative responsibility. This implies that the realization of AI's green benefits is deeply dependent on firms' internal organizational capabilities and resource endowments. Firm size, as an important proxy for organizational complexity, reflects a firm's integrated capacity for organizational coordination. Large firms typically possess stronger financial resources, enabling them to bear the trial-and-error costs associated with AI deployment; moreover, they are more likely to achieve the effect of talent accumulation, thereby fully unlocking green performance. In contrast, smaller firms often face financing constraints, insufficient absorptive capacity, and high coordination costs, making it difficult to sustain AI-driven green transformation outcomes. As firm size expands, the systemic synergy advantages conferred by organizational complexity enhance firms' ability to adapt to complex technologies, enabling AI to evolve from a localized production tool into a core technological force driving the strategic reconfiguration of corporate green efforts. Accordingly, this study proposes the following hypothesis:

H3: Once firm size reaches a certain threshold, the green enabling effect of artificial intelligence on heavily polluting manufacturing industries becomes significantly stronger.

4 Empirical Design and Data

The explanation of the indicators and their measurement methods are provided in Table 1.

Table 1. Indicator Description

Variable Type	Variable Name	<i>Var-Name</i>	Measurement
Dependent Variable	Green Transformation Level	<i>GT</i>	$\ln(\text{Green transformation keywords} + 1)$
Explanatory Variable	AI Technology Level	<i>AI</i>	$\ln(\text{AI technology word frequency} + 1)$
Mediating Variables	Labor Force Structure	<i>Labor</i>	Number of employees with master's degree o / Total employees
	Patient Capital	<i>INST</i>	Institutional investors' shareholding / Total share capital
Threshold Variable	Firm Size	<i>Size</i>	$\ln(\text{Total annual assets of the firm})$
Control Variables	Leverage Ratio	<i>Lev</i>	Year – end total liabilities / Year – end total assets
	Return on Assets	<i>ROA</i>	Net profit / Average total assets
	Cash Flow Ratio	<i>Cash-flow</i>	Net cash flow from operating activities / Total assets
	Inventory Ratio	<i>Inv</i>	Net inventory / Total assets
	Fixed Assets Ratio	<i>Fixed</i>	Net fixed assets / Total assets
	Proportion of Independent Directors	<i>Indep</i>	Independent directors / Total number of directors
	Duality	<i>Dual</i>	1 if the chairman and CEO are the same person, otherwise 0
	Listing Age	<i>ListAge</i>	$\ln(\text{Current year} - \text{Listing year} + 1)$

4.1 Descriptive Statistics

The descriptive statistical results are shown in Table 2.

Table 2. Descriptive Statistics.

<i>VarName</i>	Obs	Mean	Std.	Min	Median	Max
<i>GT</i>	5905	2.3143	0.827	0.0000	2.3979	3.9890
<i>AI</i>	5905	0.3274	0.605	0.0000	0.0000	4.4067
<i>Labor</i>	5905	3.9609	2.034	0.0000	4.0943	11.5720

<i>VarName</i>	Obs	Mean	Std.	Min	Median	Max
<i>INST</i>	5905	0.4399	0.248	0.0000	0.4638	0.9763
<i>Size</i>	5905	22.4523	1.284	19.5513	22.2593	26.7103
<i>Lev</i>	5905	0.4144	0.195	0.0108	0.4146	1.3447
<i>ROA</i>	5905	0.0539	0.066	-0.4084	0.0480	0.8796
<i>Cashflow</i>	5905	0.0588	0.071	-0.4700	0.0561	0.6641
<i>Inv</i>	5905	0.1267	0.083	0.0000	0.1087	0.6499
<i>Fixed</i>	5905	0.3025	0.150	0.0000	0.2827	0.8724
<i>Indep</i>	5905	0.3723	0.054	0.0000	0.3333	0.6667
<i>Dual</i>	5905	0.2789	0.449	0.0000	0.0000	1.0000
<i>ListAge</i>	5905	2.0171	0.911	0.0000	2.1972	3.4965

4.2 Model Construction

This study employs a two-way fixed effects model to examine the impact of artificial intelligence on the green transformation of heavily polluting manufacturing industries. The baseline regression model is specified as shown in Formula (1).

$$GT_{it} = \beta_0 + \beta_1 AI_{it} + Control_{it} + \gamma_i + \mu_t + \varepsilon_{it} \quad (1)$$

Here, GT_{it} denotes the green transformation level of heavily polluting manufacturing firm i in period t ; AI_{it} represents firm i 's artificial intelligence technology level in period t ; $Control_{it}$ denotes the control variable; γ_i and μ_t represent individual and year fixed effects, respectively; and ε_{it} denotes the error term.

This paper constructs separate mechanism models using labor force structure and patient capital as mediating variables to examine their respective roles in transmitting the impact of AI on the green transformation of heavily polluting manufacturing industries. The model specifications are presented in **Formulas (2)–(5)**.

$$Labor_{it} = \beta_2 + \beta_3 AI_{it} + Control_{it} + \gamma_i + \mu_t + \varepsilon_{it} \quad (2)$$

$$GT_{it} = \beta_4 + \beta_5 Labor_{it} + \beta_6 AI_{it} + Control_{it} + \gamma_i + \mu_t + \varepsilon_{it} \quad (3)$$

$$INST_{it} = \beta_7 + \beta_8 AI_{it} + Control_{it} + \gamma_i + \mu_t + \varepsilon_{it} \quad (4)$$

$$GT_{it} = \beta_9 + \beta_{10} INST_{it} + \beta_{11} AI_{it} + Control_{it} + \gamma_i + \mu_t + \varepsilon_{it} \quad (5)$$

Here, $Labor_{it}$ represents the proportion of highly educated personnel in heavy-polluting manufacturing enterprise i during period t , while $INST_{it}$ denotes the shareholding ratio of institutional investors in the same enterprise during period t .

The threshold effect is specifically defined as shown in **Formula (6)**.

$$GT_{it} = \alpha_0 + \alpha_1 AI_{it} \cdot I(Size_{it} \leq \theta) + \alpha_2 Salary_{it} \cdot I(Size_{it} > \theta) + Control_{it} + \gamma_i + \mu_t + \varepsilon_{it} \quad (6)$$

Here, $Size_{it}$ denotes the threshold variable; $I(\cdot)$ represents the representation coefficient, and θ indicates the threshold value.

5 Empirical Analysis

5.1 Baseline Regression

Table 3 presents the baseline regression results examining the impact of artificial intelligence on the green transformation of heavily polluting manufacturing industries. To ensure the accuracy of the regression estimates, this study adopts a stepwise approach by progressively incorporating fixed effects and control variables. Column (1) of Table 3 reports the regression without any control variables or fixed effects. Column (2) adds firm fixed effects to the specification in Column (1), while Column (3) further incorporates year fixed effects. Column (4) includes all control variables together with both firm and year fixed effects. The coefficients of the explanatory variable remain significantly positive. Taken together, these findings demonstrate that artificial intelligence exerts a significant promoting effect on the green transformation of heavily polluting manufacturing industries, thereby supporting Hypothesis 1.

Table 3. Baseline Regression.

<i>Variable</i>	(1) <i>GT</i>	(2) <i>GT</i>	(3) <i>GT</i>	(4) <i>GT</i>
<i>AI</i>	0.2649*** (15.1848)	0.3258*** (18.6139)	0.0339** (2.2535)	0.0320** (2.1213)
<i>Lev</i>				0.0673 (0.9021)
<i>ROA</i>				0.2168 (1.4899)
<i>Cashflow</i>				0.1866 (1.5152)
<i>Inv</i>				-0.5025*** (-2.7946)
<i>Fixed</i>				-0.1161 (-1.3520)
<i>Indep</i>				0.0700 (0.3629)
<i>Dual</i>				-0.0276 (-1.1518)
<i>ListAge</i>				0.0638*** (2.8286)
<i>Control</i>	2.2276*** (185.5116)	2.2091*** (229.7546)	2.3048*** (292.3109)	2.2064*** (24.7915)
<i>N</i>	5905	5895	5895	5895
<i>R²</i>	0.0376	0.5558	0.7189	0.7204
<i>Firm</i>	<i>No</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
<i>Year</i>	<i>No</i>	<i>No</i>	<i>Yes</i>	<i>Yes</i>

Note: ***, **, and * denote the 1%,5%, and 10% significance levels, respectively; the t-values are provided in parentheses, as applicable

5.2 Robustness Tests

This study conducts four sets of robustness tests to validate the baseline regression results. First, alternative measure of the explanatory variable: the natural logarithm of one plus the frequency of AI application keywords is used as an alternative proxy for artificial intelligence (*AI2*) in place of the original measure. Second, clustered standard errors: standard errors are clustered at the firm level to account for potential within-firm correlation. Third, change in sample period: the sample interval is restricted to 2017–2024. Fourth, exclusion of municipalities: firm observations from the four municipalities—Beijing, Shanghai, Tianjin, and Chongqing—are excluded from the sample, and the regressions are re-run.

Table 4 presents the results of these robustness tests. The impact of artificial intelligence on the green transformation of heavily polluting manufacturing industries remains consistently positive and statistically significant in terms of both coefficient direction and significance level, further confirming the robustness of our findings.

Table 4. Robustness Tests.

<i>Variable</i>	(1) Alternative measure of the explanatory variable <i>GT</i>	(2) Clustered stand- ard errors <i>GT</i>	(3) Change in sam- ple period <i>GT</i>	(4) Exclusion of municipalities <i>GT</i>
<i>AI2</i>	0.0639*** (4.6391)			
<i>AI</i>		0.0320** (2.1525)	0.0720*** (4.3233)	0.0388** (2.4490)
<i>Control</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
<i>N</i>	5895	5895	2892	5316
<i>R</i> ²	0.7213	0.7204	0.7981	0.7188
<i>Firm</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
<i>Year</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>

5.3 Endogeneity Test

To address potential endogeneity concerns, this study employs the first- and second-order lags of AI as instrumental variables. The regression results are reported in Table 5. The F-statistic is 56.261. The p-value for the endogeneity test is 0.8680, and the p-value for the over identification test is 0.7712. This result suggest that the estimated relationship between AI and green transformation of heavily polluting manufacturing industries is robust and that the baseline findings are not driven by significant endogeneity issues.

Table 5. Endogeneity Test.

Variable	(1)	(2)
	FE-OLS FE-2SLS	FE-OLS FE-2SLS
<i>AI</i>	0.0321* (1.71)	0.0155 (0.22)
<i>Constant</i>	2.2075*** (17.37)	
<i>N</i>	5897	3590
<i>R</i> ²	0.720	0.004
<i>Firm</i>	<i>Yes</i>	<i>Yes</i>
<i>Year</i>	<i>Yes</i>	<i>Yes</i>
<i>KP rk Wald F</i>	56.26	56.26
<i>Endog test p</i>	0.868	0.868
<i>Overid test p</i>	0.771	0.771

6 Further Analysis

6.1 Mediating Effect

Column (1) of Table 6 shows that the coefficient of *AI* is significantly positive. Column (2) reports coefficients of 0.0304 for *AI* and 0.0208 for *Labor*, both of which are statistically significant. These results indicate that AI can promote green transformation by optimising labor force structure, thereby supporting Hypothesis 2a. Column (3) of Table 6 shows that the estimated coefficient of *AI* remains significantly positive. Column (4) reveals that the coefficients of both *AI* and *INST* are significantly positive. This suggests that AI can incentivise the green transformation of heavily polluting manufacturing industries by attracting patient capital inflows, thereby supporting Hypothesis 2b.

Table 6. Mediating Mechanism Analysis.

Variable	(1)	(2)	(3)	(4)
	<i>Labor</i>	<i>GT</i>	<i>INST</i>	<i>GT</i>
<i>AI</i>	0.0795** (2.2253)	0.0304** (2.0132)	0.0052* (1.9015)	0.0300** (1.9911)
<i>Labor</i>		0.0208*** (3.5052)		
<i>INST</i>				0.3909*** (5.0418)
<i>Control</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
<i>N</i>	5895	5895	5895	5895
<i>R</i> ²	0.7416	0.7211	0.8985	0.7218
<i>Firm</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
<i>Year</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>

6.2 Threshold Effect

This paper constructs a single-threshold segmented model. The specific methodology involves: performing grid search across the 15th to 85th percentile intervals of the threshold variable; selecting the optimal threshold based on the principle of minimizing the residual sum of squares (RSS); and constructing two segmented terms, *AI_low* and *AI_high*, at the optimal threshold to verify whether their coefficients are equal. As shown in Table 7, the optimal threshold value obtained through the threshold test is 22.1547. The slope homogeneity test yielded $F=11.29$ and $p=0.0008$, significantly rejecting the null hypothesis that the coefficients of the two segments are equal. The segmented regression analysis shows that the coefficient for the high-scale interval (*AI_high*) is significantly positive, whereas the coefficient for the low-scale interval (*AI_low*) is not significant. Therefore, only when an enterprise reaches a certain scale can AI more effectively translate organizational synergy, capital investment, and management absorption capabilities into green performance. Therefore, Hypothesis 3 was confirmed.

Table 7. Threshold Effect.

<i>Variable</i>	(1)	(2)
	Linear Threshold	Linear Threshold
<i>AI_low</i>		-0.0344 (-1.37)
<i>AI_high</i>		0.0620*** (2.79)
<i>AI</i>	0.0321* (1.71)	
<i>Constant</i>	2.2075*** (17.37)	2.1831*** (17.13)
<i>N</i>	5897	5897
<i>R</i> ²	0.720	0.721
<i>Firm</i>	<i>Yes</i>	<i>Yes</i>
<i>Year</i>	<i>Yes</i>	<i>Yes</i>
<i>Threshold(Size)</i>	22.15	22.15
<i>F(diff)</i>	11.29	11.29
<i>P(diff)</i>	0.000816	0.000816
<i>F(SSR)</i>	2.048	2.048

6.3 Heterogeneity Analysis

To further investigate the impact of AI on the green transformation of heavily polluting manufacturing industries across different regions and enterprise sizes, this study conducts separate regressions based on regional development heterogeneity and enterprise size heterogeneity, aiming to provide a more comprehensive assessment of AI's applicability to green transformation.

The heterogeneity analysis of regional development levels (Columns (1) and (2) in Table 8) reveals that artificial intelligence technology primarily facilitates the green transformation of heavily polluting manufacturing industries in the eastern and central regions, with its core coefficient being significantly positive; in contrast, the *AI* core coefficient in the western region failed to pass the significance test. This is because the eastern and central regions possess relatively comprehensive digital infrastructure, highly concentrated human capital and innovation resources, as well as a stricter and more market-oriented regulatory framework. The analysis of asset size heterogeneity (Columns (3) and (4) in Table 8) reveals that AI exerts a more pronounced promoting effect on the green transformation of heavily polluting manufacturing enterprises with larger asset scales. Specifically, the *AI* core coefficient is significantly positive among manufacturing enterprises with large asset scales, whereas it fails to pass the significance test for those with small asset scales. This heterogeneous outcome strongly corroborates the threshold effect conclusion: compared to small-scale enterprises, large-scale enterprises typically possess stronger financial capabilities, more robust data foundations and R&D systems, as well as greater risk tolerance, thereby effectively driving green transformation.

Table 8. Heterogeneity Analysis.

<i>Variable</i>	(1)	(2)	(3)	(4)
	Western region	Eastern and Central regions	Large asset scale	Small asset scale
	<i>GT</i>	<i>GT</i>	<i>GT</i>	<i>GT</i>
<i>AI</i>	-0.0197 (-0.483)	0.0393** (2.422)	0.0698*** (3.703)	-0.0195 (-0.724)
<i>Control</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
<i>N</i>	884	5009	3564	2238
<i>R</i> ²	0.6716	0.7285	0.7133	0.7663
<i>Firm</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
<i>Year</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>

7 Conclusion and Policy Recommendations

7.1 Research Conclusion

Through theoretical analysis and empirical testing, this study draws the following four main conclusions.

First, baseline regression results indicate that artificial intelligence exerts a significant driving effect on the green transformation of heavily polluting manufacturing industries. This finding remains robust across a series of robustness checks. Second, mechanism analyses reveal that artificial intelligence facilitates green transformation primarily through two pathways: optimising the labor force structure and attracting patient capital inflows. Third, threshold analysis demonstrates that once firm size reaches

a certain level, the green enabling effect of AI on heavily polluting manufacturing industries becomes significantly stronger. Fourth, heterogeneity analysis shows that the green transformation effect of artificial intelligence on heavily polluting manufacturing industries is more pronounced in the eastern and central regions of China, as well as among firms with larger asset scales.

7.2 Policy Recommendations

Based on the above findings, this study proposes the following four actionable policy recommendations.

First, governments should encourage and support the application of artificial intelligence in corporate production and management processes. For heavily polluting manufacturing firms that actively adopt AI technologies, tax incentives and fiscal subsidies should be provided to promote the diffusion of AI across areas such as green technology research and development and clean energy applications. Such measures aim to achieve comprehensive upgrades of production processes, thereby reducing pollution and enhancing firms' capacity for sustainable development. Second, firms should strive to establish a high-quality talent system. On one hand, enterprises should actively promote industry-university-research collaboration with universities and research institutions to enhance their capacity for acquiring and integrating cutting-edge technological knowledge, thereby facilitating the deep integration of AI technologies with corporate production processes. On the other hand, through continuous skills training for incumbent employees, firms should strengthen the autonomous application capabilities of existing human capital in intelligent environments, achieving a synchronous upgrade of human capital and technological transformation. Third, firms should actively establish connections with external stakeholders to secure more stable sources of funding. Furthermore, enterprises should develop more detailed and standardized information disclosure systems to more effectively transmit credible signals of green development commitments. Fourth, regionally differentiated policies should be implemented to unlock comparative advantages across areas. Developed regions should focus on enhancing the quality of AI-driven green innovation, supporting enterprises in developing advanced environmental protection technologies and establishing benchmark green industrial clusters. Less developed regions should strengthen technological collaboration with developed areas, with priority support directed toward the green transformation of energy-intensive industries. These regions should also leverage their advantages in digital infrastructure and green energy to lay out integrated "AI plus new energy" projects.

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