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Artificial Intelligence, Green Transformation and New Productivity

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Abstract

First, this paper delves into the intrinsic relationship between artificial intelligence (AI) and green transformation. Given the AI composition fallacy proposed by Fang Yi et al. (2020), the AI-induced financial fraud phenomenon revealed by Chai Yanming et al. (2024), and the corporate "greenwashing" tendency discovered by Xie Haijuan et al. (2024), the relationship between the two needs to be re-examined and scientifically defined. Second, this paper systematically analyzes the intrinsic mechanisms of AI and green transformation, explaining how they synergistically promote the development of new productive forces, and conducts theoretical analysis and model construction. Finally, it proposes targeted policy recommendations, exploring how to optimize the development path of AI and green transformation to maximize synergistic effects and contribute to the development of new productive forces.

Keywords

Artificial Intelligence; New Productivity; Greenwashing.

1. Introduction

In recent years, with the rapid development of science and technology, computing power, data processing capabilities, and real-world application demands have all significantly improved. Following breakthroughs in artificial intelligence theories, its practical applications have finally ushered in a favorable development environment. Since the 20th National Congress of the Communist Party of China, the strategic position of China's modernization has become increasingly prominent. The focus of national development has shifted from an extensive growth model to a specialized and low-carbon model, and from traditional manufacturing to intelligent manufacturing-a transformation trend that is irreversible. Against this backdrop, artificial intelligence and green and low-carbon development have become two key forces driving economic and social transformation. Their coordinated development is also gradually becoming an important force in promoting national development and is of great significance for cultivating new types of productive forces.

The 2024 Government Work Report explicitly proposed implementing the "Artificial Intelligence+" action, emphasizing the deep integration and innovative application of artificial intelligence in various fields. In April 2025, the "Key Points of Digital and Green Collaborative Transformation and Development in 2025" were issued, requiring a focus on key aspects of economic transformation and upgrading and achieving high-quality development, and the improvement of the working mechanism for digital and green collaborative transformation and development. This provided policy guidance for promoting the deep integration of artificial intelligence and green transformation, and clarified the important role of digitalization and green transformation collaboration in promoting the development of new productivity.

However, while artificial intelligence (AI) and green transformation exhibit significant complementarity, they also possess inherent antagonism. On the one hand, they mutually promote each other in areas such as technological innovation and industrial upgrading; on the

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other hand, there is a contradiction between the high computing power requirements of AI and the energy conservation and emission reduction goals of green transformation. Therefore, the synergistic effect of the deep integration of AI and green transformation on cultivating new productive forces requires careful and in-depth theoretical and empirical research.

In-depth research on the synergistic mechanism between artificial intelligence and green transformation is not only helpful in solving the current energy and management challenges, but also of great significance in promoting the high-quality development of China's economy and society and assisting in the construction of Chinese-style modernization. This is highly consistent with the national strategy of comprehensive green transformation and provides new ideas and directions for achieving sustainable development. Under the framework of dual-synergy, the deep integration of artificial intelligence and green transformation can effectively cultivate and enhance new productive forces, promote the optimization and upgrading of economic structure, enhance the core competitiveness of the country, and help China gain the initiative in global science and technology and economic competition [0].

2. Literature Review

Today, with the rapid development of artificial intelligence, the cost of handling affairs and solving problems has been greatly reduced. The arduous historical task of green transformation has also reached a new level because of it [4]. With the dual support of the two, productivity has also been improved to a certain extent. In the past two years, the academic community has launched a series of discussions on this.[2]

From the perspective of artificial intelligence's impact on productivity development, Hanson (2001) argues that artificial intelligence can promote economic growth by increasing labor productivity, while Benzell (2015) believes that this is only a short-term effect, and in the long run, its substitution effect will lead to the emergence and exacerbation of poverty. Hu Ying (2023) points out that automation's empowerment of repetitive labor leads to freer and more intelligent labor relations and labor objects, which can effectively promote the development of new quality productivity.

From the perspective of the role of artificial intelligence in green transformation, Zhou Jieqi (2023) explored the significant effectiveness of artificial intelligence in the green economy, while Lü Yue (2023) emphasized the green properties of artificial intelligence in terms of carbon emissions. The degree of green transformation of enterprises is often indicated by ESG indicators, but Chinese enterprises have low disclosure levels and weak authenticity, with rampant greenwashing. Zhu Li (2024) pointed out that the emergence of artificial intelligence can reduce disclosure costs, thereby increasing financing sources and promoting green transformation.

Regarding the impact of green transformation on productivity, many foreign scholars, such as Johnstone N (2012), have pointed out that environmental regulations increase corporate costs, leading to slow development. Huang Qinghua et al. (2018) also believe that environmental regulations will reduce productivity due to increased costs, thus leading to environmental degradation. However, some domestic scholars, such as Kang Ying (2024), have pointed out that environmental regulations have an "inverted U-shaped" relationship with corporate green innovation, and the corresponding impact is also the same. Kong Lingzhang et al. (2022) have found that the development of the digital economy can significantly improve the efficiency of China's green economy.

From the perspective of the synergy between industrialization and digitalization, Wumaijiang Aishan et al. (2024) proved that there is a mutually reinforcing relationship between the two. Zhao Tianyu et al. (2024) verified that industrialization and digitalization empower China's high-quality industrial development and are a necessary way to improve the level of green

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growth in industry. Liu Yu et al. (2025) found that compared with greening or digitalization alone, industrialization and digitalization synergy can more efficiently improve the total factor productivity of enterprises.

In summary, the academic community generally holds a positive view on artificial intelligence and green transformation. However, while some explanations have been provided for the "greenwashing" behavior in promoting green transformation through artificial intelligence, the underlying practical influencing factors have not been clearly explained, and most analyses remain limited to theoretical analysis. Furthermore, the explanations and proofs regarding the antagonistic contradictions between artificial intelligence and green transformation are somewhat one-sided and require further supplementation. The mechanisms by which the two synergistically promote the development of new productive forces still need to be organized and supplemented. Additionally, the policy and program directives given regarding the practical application of artificial intelligence and the actual implementation of green transformation are outdated and require further refinement. This study will discuss and explore these aspects further.

3. Theoretical Analysis and Research Hypotheses

3.1. Analysis Summary

Specifically, since its inception in 1956, artificial intelligence has gradually developed into an independent discipline. Since the beginning of the new century, breakthroughs in theories such as neural networks have laid the foundation for the feasibility of artificial intelligence. In recent years, with the significant improvement of computing power, artificial intelligence has once again become a hot topic, profoundly changing people's lifestyles and the global economic and political landscape. However, the rapid development of artificial intelligence has also led to a sharp increase in computing power demand, resulting in heightened concerns about the energy crisis. According to the China Academy of Information and Communications Technology, by 2030, the total energy consumption of data centers in China will exceed 400 billion kilowatt-hours. If the corresponding energy consumption structure is not adjusted, it will lead to high carbon emissions [3].

At the same time, as China enters the period of capacity upgrading, the improvement of production efficiency and the strengthening of environmental regulations have made green transformation an inevitable choice for enterprises and governments.[5] Although green transformation can bring significant resource savings and optimization of allocation efficiency, its high transformation costs, slow effectiveness, high risks and limited short-term benefits have made many enterprises face challenges in the transformation process. More than two-thirds of Chinese enterprises choose not to disclose ESG (environmental, social and governance) information, but instead adopt irrational behaviors with moral risks such as "greenwashing" [6]. In this context, the application potential of artificial intelligence lies in providing low-cost solutions to alleviate the concerns of management and promote the healthy development of green transformation. However, due to the prevalence of information asymmetry and moral risks in the market, as well as the characteristics of artificial intelligence as an emotionless tool, whether its role in green transformation is to alleviate or exacerbate the problems still needs further discussion. In addition, the impact of enterprise green transformation empowered by artificial intelligence on social and economic production also needs to be thoroughly examined.

3.2. Research Hypothesis

Q1: What role does the development of artificial intelligence play in the green transformation, and how does this role come about?

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Q2: Will the development of artificial intelligence fuel the trend of "greenwashing" or suppress the bad tendencies of deceptive green transformation?

Q3: The development trend of new productivity under the synergy of artificial intelligence and green transformation.

Q4: Under the background of China's modernization, how can artificial intelligence be used to achieve the optimal results at different stages of greening?

4. Variable Design and Model Building

4.1. Variable Design

4.1.1. Green Transformation Indicators

Enterprise green transformation refers to the actions taken by enterprises to achieve harmony between themselves and the ecology through low-carbon production capacity and clean emissions. Therefore, we can learn from the green governance performance method constructed by Jiang Guangsheng et al. (2021) and then smooth it out.

First, the Janis-Fadner coefficient is used to derive Green Transformation Performance. A dictionary is created containing terms related to a company's achievements in green initiatives. A term representing gp"good performance" is defined based on this dictionary; if a term exists, it is recorded $gp = 1$, otherwise it is not $gp = 0$. Similarly, a dictionary is created containing terms related to violations of green initiatives. A term representing bp"bad performance" is defined based on this dictionary; if a term exists, it is recorded $bp = -1$, otherwise it is not $bp = 0$.

$$GTP_{it} = \begin{cases} \frac{gp\times(gp-|bp|)}{r^2}, gp > |bp|; \\ \frac{gp\times(|bp|-gp)}{r^2}, gp < |bp|; \\ 0 \qquad\qquad\qquad , gp = |bp| \end{cases} \qquad \text{Formula 1}$$

Where r represents the absolute effect, i.e.

$$r = gp + |bp| \qquad \text{Formula 2}$$

Clearly, the better the green transition performed $GTP_{it} \in [-1,1]$at that time $GTP_{it} \to 1 GTP_{it} \to -1$, the worse it performed at that time.

To reduce data interference and fluctuations and mitigate the impact of errors caused by various random factors, this study further GTP_{it}smoothed the data.

$$SGTP_{it} = \frac{1}{N}\sum_{j=1}^{N} GTP_{i,t-(j-1)} \qquad \text{Formula 3}$$

Where $SGTP_{it}$is the simple moving average of period t, $N$is the number of periods of the moving average, $GTP_{i,t-(j-1)}$and is $t-(j-1)$the actual data value of period t.

4.1.2. Artificial Intelligence Indicators

There are many methods for constructing artificial intelligence (AI) indicators in academia, most of which refer to data published by the International Federation of Robotics (IFR) and industry employment data published by national data centers. For example, Sun Wenyuan (2023) uses the per capita value of enterprise machinery and equipment as an indicator to measure the degree of AI adoption by enterprises; others use the proportion of patents with AI-

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related keywords in their names as an AI indicator, such as Yu Xinxin (2025). In view of this, this paper chooses the more representative "machine- to- labor substitution rate" as an AI indicator.

$$AI_{it} = MtLSR_{it} = \frac{SM_{it}}{SL_{it}} \quad \text{Formula 4}$$

Among them, AI_{it} the indicators are: artificial intelligence, $MtLSR_{it}$ machine-to-human value replacement rate, SM_{it} total book value of machines, SL_{it} and number of employees.

4.1.3. Construction of New Quality Productivity Indicators

The construction of new quality productivity indicators is relatively complex and difficult. Here, we draw on the method of Wang Yu (2024), which has been cited in CNKI, and use the entropy method to obtain the new quality productivity level of provincial-level administrative units across the country from 2011 to 2021 NQP_{it}.

$$x_{ij} = \frac{x_{ij} - min(x_j)}{max(x_j) - mi \ \ (x_j)} \quad \text{Formula 5}$$

$$\omega_{ij} = \frac{X_{ij}}{\sum_{i=1}^{m} X_{ij}} \quad \text{Formula 6}$$

$$e_j = -\frac{1}{ln} \times \sum_{i=1}^{m} \omega_{ij} \times ln\, \omega_i \quad \text{Formula 7}$$

$$\rho_j = 1 - e_j \quad \text{Formula 8}$$

$$\alpha_i = \frac{\rho_j}{\sum_{i=1}^{m} \rho_j} \quad \text{Formula 9}$$

Among them, e_j is the information entropy of the indicator, ρ_j is the information entropy redundancy , ω_{ij} is the indicator proportion, α_j and is the corresponding weight, from which the level of new quality productivity is obtained.

$$NQP_i = \sum_{i=1}^{m} \rho_j \quad \text{Formula 10}$$

4.2. Model Construction

(1) To examine the impact of artificial intelligence development on the green transformation of enterprises, the following panel model was constructed:

$$SGTP_{it} = \beta_0 + \beta_1 AI_{it} + Control_{it} + \theta\gamma_i + \vartheta\delta_t + \epsilon_{it} \quad \text{Formula 11}$$

Where β_0 is the fixed intercept term, β_1 is the coefficient of the explanatory variable, $Control_{it}$ is a series of control variables, γ_i is the individual fixed effect variable, δ_t is the time fixed effect variable, θ and ϑ are the coefficients of the two respectively, ϵ_{it} and is the error term.

Due to significant time-dependent effects and regional variations in policy implementation, it is necessary to set individual and time-dependent fixed terms. In addition, referring to existing literature, control variables such as firm size $size$, equity concentration $top10$, firm age age,

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firm profitability roa, degree of financing constraints SA, and debt-to-equity ratio are set $lev$to control some random factors in order to avoid significant interference.

(2) To examine the impact of artificial intelligence development and green transformation on socio-economic productivity, the following panel model was constructed:

$$NQP_{it} = \alpha_0 + \alpha_1 SGTP_{it} + \alpha_2 AI_{it} + Control_{it} + \theta\gamma_i + \vartheta\delta_t + \epsilon_{it} \qquad \text{Formula 12}$$

Here, α_0 is the fixed intercept term, α_1 and and α_2 are the coefficients of the explanatory variables. The other structures are largely similar to those in 1, and will not be repeated here. After performing the above tests, this study will also combine $SGTP_{it}$and $AI_{it}$to establish an interaction term, and use the difference-in-differences method to examine the net effect of artificial intelligence development and green transformation on socio-economic productivity.

$$NQP_{it} = \alpha_0 + \alpha_1 SGTP_{it} + \alpha_2 AI_{it} + \alpha_3 (SGTP_{it} \times AI_{it}) + Control_{it} + \theta Treated_i + \vartheta Post_t + \sigma(Post_t \times Treated_i) + \epsilon_{it} \qquad \text{Formula 13}$$

Here, $NQP_{it}$is the explained variable, i.e., a measure of new quality productivity. $Post_t$is a time dummy variable representing the time period following the implementation of the environmental regulation policy (1 after policy implementation, 0 otherwise). $Treated_i$is an individual (firm) dummy variable representing firms in the treatment group (1 for firms affected by the policy, 0 for firms in the control group). $Post_t \times Treated_i$is the core interaction term in the difference-in-differences, and its coefficient σestimates the additional change in the treatment group compared to the control group after the implementation of the environmental regulation policy, i.e., the net effect of the policy.

5. Empirical Analysis

The regression results (1) show that the regression coefficient of artificial intelligence development (AI) is 4.48e-09, and the corresponding t-statistic is 2.07, which passes the test at the 10% significance level. This result verifies the core research hypothesis of this paper, namely, that the penetration and application of artificial intelligence technology has a significant positive promoting effect on the green transformation of enterprises. From an economic perspective, for every unit increase in the level of artificial intelligence development, the green transformation index of enterprises increases by an average of 4.48e-09 units. Although the absolute value of the coefficient is small, when combined with the analysis of the actual measurement scale of the variable, if the artificial intelligence index is measured in the form of a large base such as patent stock or investment intensity, the small coefficient precisely reflects the marginal contribution characteristics of technology empowerment. More importantly, under the condition of simultaneously controlling for individual fixed effects, time fixed effects, and 15 enterprise-level control variables, the artificial intelligence coefficient still maintains statistical significance, which indicates that the technology-driven effect has strong robustness and is not caused by omitted variables or random factors.

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Table 1. Empirical analysis results

	GTPit (1)	NQPit (2)
GTPit		0.00153 *** (5.42)
AIit	4.48e-09 * (2.07)	5.67e-10*** (4.56)
Size	0.286*** (58.74)	0.000988*** (4.57)
Lev	-0.218*** (-8.23)	-0.00417** (-3.14)
ROA	3.208*** (18.82)	
ROE	0.154* (2.01)	
ATO	0.0226* (2.35)	
Cashflow	-0.172* (-2.47)	
INV	-0.348*** (-9.97)	-0.00975*** (-5.14)
FIXED	-0.274*** (-9.35)	-0.0470*** (-30.99)
Loss	0.187*** (11.83)	
Growth	0.0802*** (6.84)	-0.00186*** (-3.32)
Board	0.0250 (1.11)	
Top10	0.199*** (6.91)	
TobinQ	0.149*** (33.52)	
SOE	-0.164*** (-18.66)	-0.00574*** (-12.22)
year	0.00236* (2.16)	
_cons	-10.90*** (-5.01)	0.137*** (31.08)
N	29566	28963

The regression results (2) show that the core explanatory variables are all highly statistically significant and their signs are highly consistent with theoretical expectations, preliminarily verifying the hypothesis that artificial intelligence and green transformation have a dual empowering effect on new quality productivity. The regression coefficient of artificial intelligence development level (AI) is 5.67e-10, and the t-statistic is as high as 4.56, which is highly significant at the 1% level, indicating that artificial intelligence technology, as a general-purpose technology, has a significant positive promoting effect on social and economic productivity through multi-dimensional paths such as algorithm optimization, factor reconstruction, and business model innovation. The coefficient of green transformation index

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(GTP) is 0.00153, and the t-statistic is 5.42, which is also highly significant at the 1% level, confirming that green transformation of enterprises is not only a passive response to environmental governance, but also a strategic choice to actively cultivate new quality productivity through efficiency improvement, quality transformation, and resilience enhancement mechanisms. Moreover, its absolute value is greater than that of artificial intelligence, suggesting that the productivity effect of green transformation may have a more direct economic manifestation during the sample period. Regarding control variables, the coefficient for firm size (Size) was 0.000988 and significantly positive at the 1% level, but the value was small, indicating that the cultivation of new productivity relies more on quality-based rather than scale-based factors; the coefficient for debt-to-equity ratio (Lev) was -0.00417 and significantly negative at the 5% level, verifying the inhibitory effect of financial constraints on high-risk innovation investment; the inventory ratio (INV) and fixed asset ratio (FIXED) showed significant negative effects of -0.00975 and -0.0470, respectively, with the latter having the strongest t-statistic of -30.99, revealing that the sunk costs locked in by traditional heavy asset operations are... The deep-seated structural obstacles to the leap in new-quality productivity; the coefficient of operating revenue growth rate (Growth) is -0.00186 and significantly negative at the 1% level, which contrasts sharply with the positive effect in the green transformation model, profoundly revealing the inherent tension between the speed of traditional scale expansion and the quality orientation of new-quality productivity; the coefficient of the shareholding ratio of the top ten shareholders (Top10) is 0.0212 and highly significant, highlighting the key role of long-term strategic investors, while the coefficient of the state-owned enterprise dummy variable (SOE) is -0.00574 and significantly negative, indicating that insufficient innovation incentives caused by institutional factors have constrained the transformation of state-owned economy into new-quality productivity.

6. Policy Implications and Conclusion

We will vigorously support the research and application of artificial intelligence technology, give full play to its enormous potential in promoting social progress and economic development, and guide artificial intelligence technology to develop in a direction that is conducive to human well-being and promotes social fairness and harmony by formulating sound laws, regulations and industry standards, so that it can better serve the people and bring convenience and improvement to people's lives.

We must fully recognize the dual nature of artificial intelligence technology. While actively leveraging its advantages to promote green transformation and enhance new productivity, we must be wary of the potential risks and challenges it may bring. However, the most negative aspect for the government is that individuals and businesses may use it as a tool to commit crimes, violate regulations, and harm the general public.

The government should encourage enterprises to use artificial intelligence correctly and rationally, and to keep up with the times. Enterprises should not treat artificial intelligence as a new protective umbrella under the sun, but rather as a timely shelter from the rain. They should also strive to be at the forefront of the application of advanced tools, work hard to improve resource allocation, and thereby increase social welfare.

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