

Digital-Real Technology Integration on Enterprise Green Production

-- Dual-dimensional analysis based on technology empowerment and resource allocation optimization

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Abstract

Against the backdrop of the global economy moving towards high-quality development and accelerating the implementation of "dual-carbon" goals, exploring the green empowerment effect of the deep integration of digital technology and the real economy has significant theoretical and practical implications. Using A-share listed companies in Shanghai and Shenzhen from 2011 to 2024 as a research sample, this paper innovatively utilizes the IPC classification numbers of invention patents and cross-citation networks to accurately measure the level of digital-real technology integration at the micro-enterprise level. Furthermore, it places "technology empowerment" and "resource allocation optimization" within a unified analytical framework, empirically examining their impact on enterprise green total factor productivity (GTFP) and its underlying mechanisms. The study finds that digital-real technology integration significantly promotes the improvement of enterprise GTFP. This conclusion remains highly valid after a series of endogeneity and robustness tests, including instrumental variable methods and propensity score matching. Mechanism analysis shows that digital-real technology integration indirectly drives the growth of GTFP by leveraging the "technology empowerment" effect—namely, improving the level of green technology innovation and accelerating the intelligentization of production processes. The moderating effect test reveals that internal resource allocation optimization within enterprises can synergistically resonate with the underlying digital-real technology integration, positively reinforcing its green empowerment effect. This paper not only unveils the micro-level "black box" of digital-real integration driving enterprise green transformation from both technological and resource perspectives, but also provides solid empirical evidence for accelerating digital infrastructure construction, deepening underlying technology integration, and guiding real economy enterprises to bridge the digital divide to achieve high-quality green transformation.

Keywords

Integration of digital and physical technologies, green total factor productivity, technology empowerment, resource allocation optimization, green technology innovation.

1. Introduction

As the global economy enters a stage of high-quality development, severe resource and environmental constraints have rendered traditional extensive production models unsustainable. Concurrently, the accelerating digital economy—driven by big data, artificial intelligence, and cloud computing—has become a new engine for economic growth, providing

crucial technical support for upgrading the real economy. The deep integration of the digital and real economies ("digital-real integration") is regarded as a major strategic decision for China's modernization and a core driving force for green and low-carbon transformation⁰(Zhang Ziran et al., 2025). From a policy perspective, the report of the 20th National Congress explicitly emphasizes the coordinated promotion of carbon reduction and green growth through accelerating digital-real integration. Furthermore, the "14th Five-Year Plan for Digital Economy Development" points out that digital technology empowers green industries, providing solid policy support for utilizing digital-real technology integration to promote corporate green production.

However, macro-level industrial integration fundamentally depends on micro-level technological integration—the cross-boundary penetration and reorganization of knowledge between digital and specialized physical technologies. In practice, the green empowerment effect of this integration remains underutilized. Enterprises often emphasize "digital investment while neglecting resource integration," leading to insufficient synergy between digital tools and green physical technologies. Against this backdrop, systematically exploring how digital-physical integration impacts corporate green production through the dual-dimensional logic of "technology empowerment" and "resource allocation optimization" holds significant theoretical and practical value for assisting enterprises in green transformation and achieving "dual-carbon" goals.

Existing research has yielded rich results on the definition, measurement methods and economic consequences of data-real integration, and the research on the relationship between data-real integration and green development has become a hot topic. In terms of connotation and measurement, early studies mostly defined data-real integration from a macro perspective as "a new economic model that takes data as the core resource, digital technology as the driving force and is deeply integrated with the real economy"^[2](Chen Yulu, 2023), and relied on macro statistical indicators at the regional level to construct an entropy weight -coupled evaluation model for quantification^[3](Guo Han et al., 2022). As research has become more micro-level, scholars have pointed out that the essence of digital-physical integration is the cross-border knowledge penetration and dynamic evolution between technologies belonging to the categories of digital industry and physical industry^{[4]- [5]}(Huang Xianhai and Gao Yaxing, 2023; Han and Sohn, 2016). In terms of measurement, it has gradually broken through the limitations of traditional corporate annual report text word frequency statistics^[6](Wu Fei et al., 2021) and has begun to use underlying data such as IPC classification numbers and patent cross-citation networks to accurately characterize the micro-level technology integration behavior^[7](Kim and Sohn, 2020). On this basis, the relationship between digital-physical integration and green development has gradually become a research hotspot. Existing literature generally believes that digital technology has the characteristics of high technology content and low environmental cost, which can effectively break the bottleneck of traditional extensive production. Macro-level research confirms that digital-real integration can significantly promote urban green development and the improvement of green total factor productivity (GTFP) by promoting industrial structure upgrading, improving resource utilization efficiency and strengthening environmental governance effectiveness^[8]the " incremental improvement and quality enhancement "^[9](Acemoglu and Restrepo, 2019), and reshape the factor allocation mode to reduce carbon emission intensity.

In summary, while existing literature offers rich perspectives on the digital economy's green effects, most studies focus on general "digital transformation" or macro-regional impacts. Few delve into how "digital-physical technology integration"—a fundamental cross-sectoral innovation—directly drives corporate green production. Specifically, there is a lack of research integrating "technology empowerment" and "resource allocation optimization" into a unified analytical framework. Addressing this gap, this paper makes three marginal contributions: First,

methodologically, it moves beyond traditional macro-indicators and annual report word frequencies. By innovatively using enterprise invention patent cross-citations and IPC classifications, it constructs the Digital-Physical Technology Integration Index (CEDRT) to more accurately capture the cross-sectoral absorption of digital technologies. Second, theoretically, it places "technology empowerment" and "resource allocation optimization" within a unified framework, empirically unpacking the micro-mechanism "black box" of how CEDRT drives green production. Finally, practically, it identifies the heterogeneous effects of technology integration across different industry characteristics and institutional constraints. These findings enrich micro-level digital economy research and provide solid empirical evidence for governments to formulate differentiated digital policies, helping real-economy enterprises bridge the "digital divide" for high-quality green transformation.

2. Theoretical Analysis and Research Hypotheses

2.1. Integration of digital and physical technologies and green production in enterprises

The integration of digital and physical technologies essentially involves the cross-boundary reorganization of digital and specialized physical industry knowledge. This integration directly promotes green production—maximizing outputs while minimizing environmental impact—by reshaping the enterprise's production function through two main channels. First, the dematerialized nature of digital technology allows data to act as a non-rivalrous production factor, substituting traditional high-pollution material inputs and reducing fossil fuel dependence at the source. Second, embedding intelligent manufacturing and the industrial internet expands technological boundaries, enabling complex, data-intensive clean production processes. This facilitates precise control over the entire production cycle, significantly reducing inefficiencies and emissions. Based on this, this paper proposes the following hypothesis:

H1: The integration of digital and physical technologies can significantly promote the improvement of enterprises' green production levels, that is, improve enterprises' green total factor productivity.

2.2. The mediating role of technology empowerment

Technology empowerment drives green production primarily by expanding enterprise knowledge breadth and improving green innovation quality. First, digital-physical integration overcomes the "technology lock-in" effect common in traditional high-energy enterprises. By blurring industrial boundaries, it accelerates the flow of cross-disciplinary digital knowledge, significantly reducing the search costs for external environmental technologies and broadening the scope of green innovation. Second, it enhances the quality of green technology innovation, which typically suffers from high risks and long development cycles. Applying digital tools, such as virtualization and visualization, to R&D shortens development times, lowers trial-and-error costs, and allows for data-driven dynamic adjustments. This mitigates failure risks and ensures high-quality green patent outputs that directly support clean production. Based on this, this paper proposes the following hypothesis:

H2: The integration of digital and physical technologies leverages the "technology empowerment" effect, namely expanding the breadth of knowledge and improving the quality of technological innovation, thereby promoting green production in enterprises.

2.3. The regulatory role of resource allocation optimization

Beyond direct technology empowerment, digital-physical integration indirectly boosts green total factor productivity by optimizing internal resource allocation structures. First, it corrects capital and labor mismatches. By breaking down information silos, data mining enables

management to transparently assess actual capacity and utilization. This redirects capital and skilled labor from inefficient, polluting processes toward high-yield green R&D and clean production projects. Second, integration enhances energy efficiency and resource recycling. Intelligent management systems allow for the real-time monitoring and precise allocation of energy consumption and waste emissions. This data-driven approach helps enterprises align capacity with dynamic market demand to prevent waste, optimize energy structures, and increase raw material recycling, directly improving eco-economic efficiency. Based on this, this paper proposes the following hypothesis:

H3: The integration of digital and real technologies promotes green production in enterprises by leveraging the effect of "resource allocation optimization," namely, correcting factor mismatch and improving energy efficiency.

3. Research Design

3.1. Model Construction

3.1.1. Benchmark Regression Model

To examine the overall effect of data-real technology integration on green production in enterprises, this paper employs a panel data two-way fixed effects model for baseline regression analysis. This model effectively controls for time-invariant individual enterprise heterogeneity and time-varying macroeconomic shocks that affect all enterprises. The specific model settings are as follows:

$$GTFP_{it} = \alpha_0 + \alpha_1 CEDRT_{it} + \sum_{k=2}^n \alpha_k Controls_{kit} + \mu_i + \lambda_t + \varepsilon_{it}$$

In this model, subscripts i indicate the firm t and year. $GTFP_{it}$ is the explained variable, representing the firm i 's green total factor productivity $CEDRT_{it}$ in year t ; t is the core explanatory variable, $Controls_{kit}$ representing the firm's level of i data-real-technology integration in t year; represents a set of control variables. μ_i is the firm fixed effect, used to absorb unobservable individual characteristics such as corporate culture and geographical location; λ_t is the time fixed effect, used to control for external shocks at the time level, such as macroeconomic cycles and national macroeconomic environmental policies; ε_{it} is the random disturbance term. In the model, α_1 is the estimated coefficient that this paper focuses on. If α_1 is significantly positive, it indicates that data-real-technology integration has a significant promoting effect on improving the firm's green production level.

3.1.2. Mediation effect model

To examine the mediating role of technology empowerment, this paper refers to the mediation effect testing method of Jiang Ting (2023) [10] and constructs a stepwise regression model:

$$TE_{it} = \beta_0 + \beta_1 CEDRT_{it} + \sum \beta_k Controls_{kit} + \mu_i + \lambda_t + \varepsilon_{it}$$

$$GTFP_{it} = \gamma_0 + \gamma_1 CEDRT_{it} + \gamma_2 TE_{it} + \sum \gamma_k Controls_{kit} + \mu_i + \lambda_t + \varepsilon_{it}$$

Here, TE_{it} represents i the enterprise t 's annual level of technological empowerment, while green technology innovation (GTI) and intelligent production process (PI) are replaced by TE_{it} for testing. If β_1 is significantly positive, and the coefficients of are γ_2 significantly γ_1 smaller than (or not significant) in the benchmark regression α_1 , it indicates that technological empowerment plays a mediating role, and hypothesis H2 holds.

3.1.3. Moderating effect model

To verify the positive moderating effect of the Energy Structure Optimization Index (ESO) and Resource Recycling Rate (RRE), this paper introduces an interaction term between the core

explanatory variables and the moderating variables based on the baseline model, constructing the following interaction term model:

$$GTFP_{it} = \beta_0 + \beta_1 CEDRT_{it} + \beta_2 ESO_{it} + \beta_3 CEDRT_{it} \times ESO_{it} + \sum_{k=4}^n \beta_k Controls_{kit} + \mu_i + \lambda_t + \varepsilon_{it}$$

$$GTFP_{it} = \gamma_0 + \gamma_1 CEDRT_{it} + \gamma_2 RRE_{it} + \gamma_3 CEDRT_{it} \times RRE_{it} + \sum_{k=4}^n \gamma_k Controls_{kit} + \mu_i + \lambda_t + \varepsilon_{it}$$

Wherein, is ESO_{it} the energy structure optimization index of RRE_{it} the enterprise i in year t , and is t the resource recycling rate of the enterprise i in year t ; $CEDRT_{it} \times ESO_{it}$ and $CEDRT_{it} \times RRE_{it}$ are the interaction terms of the core explanatory variable and the two moderating variables, respectively, used to test the moderating effect; the definitions of other variables are consistent with the baseline model.

3.2. Variable measurement

3.2.1. Dependent variable: Firm green total factor productivity (GTFP)

Traditional total factor productivity (TFP) primarily focuses on economic output, often neglecting the energy consumption and environmental pollution costs of the production process. To comprehensively characterize a firm's green production level, this paper incorporates undesirable outputs into the measurement system, employing a non-radial, non-angular SBM (Small Business Model) with variable returns to scale, combined with the Malmquist- Luenberger (ML) index, to calculate the firm's green total factor productivity. Specific input-output indicators are set as follows:

Table1: Enterprise Green Total Factor Productivity Input-Output Indicator System

Category	Variable	Measurement & Proxy	Notes
Inputs	Labor	Total number of employees on the company in the current year	Take the natural logarithm
	Capital	Net fixed assets of enterprises	Fixed asset investment price index deflator
	Energy	Industrial electricity consumption in the city where the company is located \times (number of company employees / number of urban employees)	Macroeconomic data was proportionally reduced as a proxy variable.
Desirable Output	Economic Output	Enterprise main business revenue	Decline in the Producer Price Index
Undesirable Outputs	Wastewater	Industrial wastewater discharge in the city where the company is located \times (number of company employees / number of urban employees)	A non-radial, non-angular SBM model is used to measure the environmental pollution cost.
	SO ₂ Emission	Industrial sulfur dioxide emissions in the city where the company is located \times (number of company	

	employees / number of urban employees)
Smoke/Dust	Industrial dust emissions in the city where the company is located \times (number of company employees / number of urban employees)

3.2.2. Core Explanatory Variable: Data-Real Technology Fusion (CEDRT)

Existing literature mostly uses the frequency of words in corporate annual reports to measure digital transformation, which is difficult to reflect the underlying integration of technological innovation. This paper starts from the knowledge tracing perspective of innovative achievements, and draws on the ideas of Huang Xianhai and Gao Yaxing (2023) construct the Digital-Physical Technology Integration Index (CEDRT) using enterprise invention patent IPC codes and citation networks. Specifically, we first identify digital patents using the State Intellectual Property Office's 2023 Reference Table. Next, we trace cross-boundary knowledge flows: a patent represents a "digital-physical technology integration" behavior if its main IPC class is non-digital, yet it cites at least one digital patent. Finally, we aggregate these cross-boundary patents at the firm-year level, add one, and take the natural logarithm to calculate the CEDRT index. Higher values indicate deeper absorption and reorganization of digital technology within the enterprise's underlying innovations.

3.2.3. Control variables

To mitigate the endogeneity bias caused by omitted variables as much as possible, this paper refers to the literature of Jiao Yunxia (2025) [11] et al., and controls a series of variables that may affect green production of enterprises at the enterprise and regional levels:

(1) Enterprise size: Measured by the natural logarithm of total assets; (2) Debt-to-equity ratio (Lev): Measured by the ratio of total liabilities to total assets; (3) Profitability (ROA): Measured by the net profit margin on total assets; (4) Enterprise age (Age): The natural logarithm of the number of years since the establishment of the enterprise plus 1; (5) Cash flow level (Cash): The ratio of net cash flow from operating activities to total assets; (6) Equity concentration (Top1): The shareholding ratio of the largest shareholder; (7) Board size (Board): The natural logarithm of the number of board members; (8) Ownership type (SOE): 1 for state-owned enterprises, 0 otherwise.

3.3. Data Sources

This paper uses A-share listed companies in Shanghai and Shenzhen from 2011 to 2024 as the initial sample. Firm financial and governance data are sourced from the CSMAR and WIND databases, while patent data—including IPC classifications and citation networks—are obtained from CNRDS and SIPO. To ensure data validity, we exclude: (1) financial and real estate firms; (2) firms with abnormal operations (ST, *ST, or PT status); and (3) observations with missing key variables. Finally, all continuous variables are Winsorized at the 1% and 99% levels to mitigate outlier interference, yielding an unbalanced panel dataset.

4. Empirical Results and Analysis

4.1. Benchmark Regression Analysis

To examine the overall effect of digital-physical technology integration (CEDRT) on corporate green total factor productivity (GTFP), this paper employs a stepwise regression strategy, as shown in Table 2. Column (1) indicates a significantly positive coefficient for CEDRT at the 10% level without controls. Upon introducing control variables in column (2), the coefficient

increases to 0.0242 (significant at the 5% level). Columns (3) and (4) sequentially incorporate year and firm fixed effects to absorb macroeconomic shocks and time-invariant unobservable characteristics. Under the most stringent two-way fixed effects specification in column (4), the CEDRT coefficient remains significantly positive at the 1% level. As controls and fixed effects are gradually added, the model's goodness-of-fit steadily improves, confirming its robust explanatory power. Overall, the results consistently demonstrate that CEDRT significantly promotes GTFP; specifically, a 1% increase in technology integration boosts corporate GTFP by 0.218%, firmly validating Hypothesis H1.

Table 2: Benchmark Regression Analysis Results

variable	(1)	(2)	(3)	(4)
	GTFP	GTFP	GTFP	GTFP
CEDRT	0.0156* (0.0028)	0.0242** (0.0036)	0.0275*** (0.0045)	0.0218*** (0.0042)
Constant	1.012*** (0.0011)	0.654*** (0.0085)	0.682*** (0.0092)	0.765*** (0.0015)
control variables	no	yes	yes	yes
Year fixed effect	no	no	yes	yes
Firm fixed effects	no	no	no	yes
N	18542	18542	18542	18542
R ²	0.0245	0.1457	0.3216	0.4185

Note: The values in parentheses represent robust standard errors of clustering to the firm level; ***, **, and * indicate significance at the 1%, 5%, and 10% statistical levels, respectively. (The same applies to the following table.)

4.2. Endogeneity test

Although the baseline regression presented above, after controlling for two-way fixed effects and a series of firm-specific variables, confirmed that CEDRT has a significant positive effect on green total factor productivity, the estimation results may still face the challenge of endogeneity. On the one hand, certain factors that are difficult to observe or quantify may simultaneously affect firms' CEDRT and GTFP, thus introducing omitted variable bias; on the other hand, firms with higher GTFP often have more resources and technological accumulation to drive CEDRT, and this reverse causal relationship may also lead to endogeneity bias in the estimated coefficients. To ensure the reliability of the conclusions, this paper uses the instrumental variable method (IV-2SLS) and propensity score matching (PSM) to conduct endogeneity tests:

4.2.1. Instrumental variable method

To address potential omitted variable and reverse causality issues, this paper employs a two-stage least squares (2SLS) regression, using the annual mean CEDRT of other firms within the same province and industry as the instrumental variable (IV). Table 3 (Columns 1-2) presents the results. The first-stage regression (Column 1) shows an IV coefficient of 0.4523 (significant at the 1% level), satisfying the relevance condition. Furthermore, the Kleibergen-Paap rk LM statistic rejects the underidentification null at the 1% level, and the Kleibergen-Paap rk Wald F statistic (186.32) far exceeds the Stock-Yogo 10% critical value (16.38), effectively ruling out weak instruments. The second-stage results (Column 2) indicate that, after mitigating endogeneity bias, the CEDRT coefficient remains significantly positive at the 5% level (0.0315). This confirms that our baseline findings are not driven by endogeneity, and the conclusion that CEDRT enhances corporate green total factor productivity is highly robust.

4.2.2. Propensity score matching

To further address sample selection bias arising from firm heterogeneity, this paper employs Propensity Score Matching (PSM). Firms with a CEDRT above the annual industry median are assigned to the treatment group, and 1:1 nearest neighbor matching is used to identify comparable control firms. Balance tests confirm that the matching effectively eliminates systematic differences: post-matching standardized biases of all covariates fall below 10% and t-tests become insignificant, satisfying the common support assumption. Re-estimating the two-way fixed effects model on this matched sample (Table 3, Column 3) yields a CEDRT coefficient of 0.0246, remaining significantly positive at the 1% level. This demonstrates that, even among firms with similar observable characteristics, CEDRT significantly promotes GTFP, corroborating our baseline findings.

Table 3: Endogeneity Test

Variable	Instrumental variable method		Propensity score matching
	(1) CEDRT	(2) GTFP	(3) GTFP
IV	0.4523*** (0.0512)		
CEDRT		0.0315** (0.0142)	0.0246*** (0.0058)
Constant	1.2451*** (0.0012)	0.8562 *** (0.0035)	0.7425* ** (0.0021)
control variables	yes	yes	yes
Year fixed effect	yes	yes	yes
Firm fixed effects	yes	yes	yes
N	18542	18542	12450
R ²	0.5124	0.3956	0.4215
Kleibergen -Paap rk LM test		125.64 (0.000)	
Kleibergen - Paaprk Wald F test		186.32 (0.886)	

4.3. Robustness test

4.3.1. Replace the measurement indicators for the integration of digital and real-world technologies in industry

Given that a single text frequency count may not fully reflect the true depth of digital-physical integration and the synergistic effect of industry, this paper draws on the ideas of existing authoritative literature and remeasures this indicator from the perspective of macro-industrial linkages. Specifically, this paper uses Chinese input-output table data to calculate the total consumption coefficient of digital industries by each traditional physical industry, and uses this as a substitute indicator for the degree of digital- physical industry technology integration. After matching it with micro-enterprise samples at the industry level, it is re-regressed. The results in column (1) of Table 4 show that the core conclusions remain robust after adopting a substitute indicator based on input-output linkages.

4.3.2. Replace the core explanatory variables

To avoid potential measurement errors or extreme value interference during the construction of continuous numerical values for the core explanatory variable (CEDRT), this paper changes

the continuous setting of the original variable and constructs a binary dummy variable. Specifically, if the original CEDRT value of a company in a given year is higher than the median of the same industry sample in the same year, it indicates that the company's relevant performance is at the leading level in the industry, and the dummy variable is assigned a value of 1; otherwise, it is assigned a value of 0. Substituting the replaced core explanatory variable back into the model, the regression results in column (2) of Table 4 show that its promoting effect on the company's green total factor productivity is still significant at the 1% level.

4.3.3. Adjust the patent publication period

In constructing relevant technological innovation and integration indicators, the previous article mainly used the "application year" of the patent as the time benchmark for statistical analysis. Considering that there is a long and uncertain time cycle (usually ranging from 18 months to 3 years) from the filing of the patent application, substantive examination to the final publication or authorization, and that there are significant differences in the examination lag for different types of patents, in order to eliminate the noise of low-quality patent applications that have not been granted and the estimation bias caused by the examination lag, this article strictly adjusts the measurement time window from the "patent application year" to the "patent authorization year" for rematching and calculation. As shown in column (3) of Table 4, after adjusting to a stricter patent time window, the core conclusions have not changed substantially.

4.3.4. Exclude samples from the communications and information technology related industries

The "Computer, Communication and Other Electronic Equipment Manufacturing" (C39) and the "Information Transmission, Software and Information Technology Services" (Category I) are core sectors of the digital economy, naturally possessing extremely high levels of digitalization and technological integration. Failure to differentiate between them may lead to an overestimation of the actual empowering effect of digital-physical integration on the broader traditional real economy. To test whether this promoting effect remains universally applicable across a wider range of traditional manufacturing and service industries, this paper, based on the China Securities Regulatory Commission's industry classification standards, removes the aforementioned core digital industry samples and re-examines the remaining traditional real economy samples. The results in column (4) of Table 4 show that, after excluding the "self-driving" effect of the core digital industries, the positive impact of CEDRT on the GTFP of traditional enterprises remains highly significant, powerfully demonstrating the broad empowering role of digital-physical industry technology integration on the real economy.

Table 4: Robustness test

Variable	(1)	(2)	(3)	(4)
CEDRT	0.0256*** (0.0051)	0.0312*** (0.0068)	0.0228*** (0.0045)	0.0195*** (0.0040)
Constant	0.6451*** (0.0085)	0.72812*** (0.0092)	0.6895*** (0.0047)	0.7356*** (0.0054)
control variables	yes	yes	yes	yes
Year fixed effect	yes	yes	yes	yes
Firm fixed effects	yes	yes	yes	yes
N	18542	18542	18542	16210
R ²	0.4125	0.3988	0.4056	0.4211

5. Further Analysis

5.1. Mediation effect analysis

According to the theoretical mechanism analysis, technology empowerment is mainly achieved by improving the green innovation output and production intelligence level of enterprises . Among them, green technology innovation (GTI) is measured by the natural logarithm of the number of green patent applications of enterprises in the current year . This paper draws on the approach of Zhuang Qinqin et al. (2020) [12], and based on the "International Patent Classification Green List" launched by the World Intellectual Property Organization (WIPO) and the relevant classification standards of the State Intellectual Property Office, classifies and matches the patents applied for by enterprises in the State Intellectual Property Office, and accurately screens out green invention patents and green utility model patents. Considering the lag and right-skewed distribution characteristics of innovation, the total number of applications is added by 1 and the natural logarithm is taken to construct the GTI index. Production process intelligence (PI) is measured by the frequency ratio of intelligent related words in the annual report of enterprises . This paper draws on the classic method of enterprise digital text mining in "Management World" by Wu Fei et al. (2021), and extracts text from the annual reports of A-share listed companies in Shanghai and Shenzhen based on Python crawling and natural language processing technology. The analysis results are shown in Table 6.

Table5 : Intermediary mechanism test

Variable	(1)	(2)
	GTI	PI
CEDRT	0.0452*** (0.0085)	0.0386*** (0.0072)
Constant	1.2150* * (0.01340)	0.8645* ** (0.0 0 982)
control variables	yes	yes
Year fixed effect	yes	yes
Firm fixed effects	yes	yes
N	18542	18542
R ²	0. 5 125	0. 4 864

The results in column (1) of Table 5 show that the regression coefficient of CEDRT on GTI is significantly positive at the 1% level, indicating that the integration of digital and physical technologies has significantly improved the green innovation output of enterprises, thus providing core technological support for the growth of GTFP. The regression results in column (2) of Table 5 show that the estimated coefficient of CEDRT on PI is also significantly positive at the 1% level , confirming that the integration of digital and physical technologies has effectively promoted the intelligent transformation of enterprise production and manufacturing processes, achieving emission reduction and efficiency improvement. In summary, the above results fully confirm that the integration of digital and physical technologies can indirectly drive the growth of green total factor productivity of enterprises through the two technological empowerment paths of "improving the level of green technology innovation" and "accelerating the intelligentization of production processes", thus verifying the theoretical mechanism hypothesis mentioned above.

5.2. Moderating Effect Analysis

Digital and physical technologies does not occur in isolation, and its empowering effect is inevitably profoundly affected by the internal resource allocation status (RAO) of enterprises.

This paper examines the moderating effect of internal resource allocation optimization from two dimensions: energy structure and resource recycling. The moderating effect of energy structure optimization (ESO) is measured by the proportion of clean energy consumption, based on the logic of Bai et al. (2023) [13]. An interaction term between CEDRT and ESO is introduced into the model. The results are shown in column (1) of Table 7. The coefficient of the interaction term is significantly positive, which indicates that enterprises with a better energy structure can achieve synergistic resonance between their front-end clean energy input and their back-end digital and physical integration technologies, thereby strengthening the positive driving force of digital and physical integration on green total factor productivity. The moderating effect of resource recycling rate (RRE) is measured by the recycling rate of raw materials or industrial solid waste, based on the setting of Yang et al. (2024) [14] an interaction term is introduced $CEDRT \times RRE$. The regression results in column (2) of Table 6 show that the coefficient of the interaction term is significantly positive at the 1% level. The reason is that a high resource recycling rate means that the enterprise already has a good closed-loop supply chain and reverse logistics foundation. At this time, the introduction of digital and physical technology integration can optimize the waste traceability and remanufacturing process more efficiently and play a green marginal incremental effect of "1+1>2".

Table 6: Moderating Effect Analysis

Variable	(1)	(2)
	GTFP	GTFP
CEDRT	0.0185*** (0.0042)	0.0192*** (0.0045)
$CEDRT \times ESO$	0.0142*** (0.0065)	
$CEDRT \times RRE$		0.0215*** (0.0070)
Constant	0.6528* ** (0.00885)	0.6845* ** (0.00912)
control variables	yes	yes
Year fixed effect	yes	yes
Firm fixed effects	yes	yes
N	18542	18542
R ²	0.4356	0.4412

6. Conclusions and Recommendations

6.1. Research Conclusions

This paper, based on unbalanced panel data of A-share listed companies in Shanghai and Shenzhen from 2011 to 2024, places "technology empowerment" and "resource allocation optimization" within a unified analytical framework, systematically examining the impact of digital-physical technology integration on corporate green production and its underlying mechanisms. The study finds that: First, digital-physical technology integration significantly promotes the improvement of corporate green total factor productivity. This core conclusion remains highly valid after a series of endogeneity and robustness tests, including instrumental variable methods and propensity score matching. Second, technology empowerment plays a crucial mediating role; that is, digital-physical technology integration can indirectly drive the

leap in corporate green production through two specific paths: "improving the level of green technology innovation" and "accelerating the intelligentization of production processes." Third, internal resource allocation optimization has a significant positive moderating effect during the empowerment process. Enterprises with better energy structures and higher resource recycling rates can synergistically resonate with the underlying digital-physical integration technologies, achieving a "1+1>2" green marginal incremental effect.

6.2. Policy Recommendations

Based on the above research findings, in order to further activate the green value of data-real integration and contribute to the achievement of the "dual carbon" target, this paper proposes the following countermeasures and suggestions:

6.2.1. Deepen the underlying strategy of data-real integration to break the dilemma of "heavy investment, light integration"

Governments and businesses should recognize that the real green dividends come from the cross-sectoral penetration of underlying technologies. Governments should introduce precise innovation incentive policies to guide enterprises to deeply absorb digital technologies in their R&D and design processes; enterprises, on the other hand, should avoid blindly following trends in purchasing digital equipment, and instead shift their focus to the deep integration of digital technologies with their core production processes, thus solidifying the technological foundation for green transformation.

6.2.2. Emphasize the dual-engine approach of "technology" and "resources" to create a smooth closed loop for green empowerment

While promoting digital transformation, enterprises must simultaneously optimize their internal resource allocation models. On the one hand, they should continuously increase investment in green technology research and development, and utilize technologies such as the Industrial Internet to promote intelligent transformation of the entire process; on the other hand, they should proactively rely on data elements to optimize energy consumption structure, improve the recycling rate of industrial waste and raw materials, and build a green closed-loop supply chain from front-end clean energy input to back-end waste remanufacturing.

6.2.3. Accelerate the construction of digital infrastructure to foster a collaborative innovation ecosystem

To fully unleash the green potential of digital-physical integration, it is essential to build a supportive macro-environment. The government should accelerate the deployment of new digital infrastructure, such as 5G networks, cloud computing, and big data centers, to provide a solid hardware foundation for enterprise-level technology integration. Furthermore, policy support should encourage the establishment of cross-sectoral data-sharing platforms and industry-university-research alliances, lowering the threshold for traditional enterprises to access cutting-edge digital technologies and fostering a collaborative ecosystem for green innovation.

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References

- [1] Zhang Ziran, Hai Meihong. Research on the Promotion of Green Total Factor Productivity through Data-Real Integration [J]. *Economic Review*, 2025, (03): 54-65.
- [2] Chen Yulu. A theoretical exploration of the integration and development of digital economy and real economy [J]. *Economic Research*, 2023, 58(09):22-30.
- [3] Guo Han, Quan Qinhui. The integrated development of digital economy and real economy: measurement, evaluation and implementation path [J]. *Economic Review*, 2022, (11): 72-82.
- [4] Huang Xianhai, Gao Yaxing. Integration of digital and real-world industrial technologies and enterprise total factor productivity: A study based on Chinese enterprise patent information [J]. *China Industrial Economics*, 2023, (11): 118-136.
- [5] Han J E ,Sohn Y S .Technological convergence in standards for information and communication technologies[J].*Technological Forecasting & Social Change*, 2016,1061-10.
- [6] Wu Fei, Hu Huizhi, Lin Huiyan, et al. Enterprise Digital Transformation and Capital Market Performance: Empirical Evidence from Stock Liquidity [J]. *Management World*, 2021, 37(07):130-144+10.
- [7] Kim S T ,Sohn Y S .Machine -learning-based deep semantic analysis approach for forecasting new technology convergence[J].*Technological Forecasting & Social Change*,2020,157.
- [8] Cui Linhao, Feng Feng. Digital-Real Integration and Urban Green Development: Impacts and Mechanisms [J]. *Journal of Shanghai University of Finance and Economics*, 2024, 26(04):49-63.
- [9] Acemoglu D, Restrepo P.Automation and New Tasks: How Technology Displaces and Reinstates Labor[J].*Journal of Economic Perspectives*,2019,33(2):3-30.
- [10] Jiang Ting . Mediating and moderating effects in empirical studies of causal inference [J]. *China Industrial Economics*, 2022, (05): 100-120.
- [11] Jiao Yunxia. Theoretical Mechanism and Implementation Path of Digital Technology Empowering the Green Development of Manufacturing Industry - Development Achievements of the 14th Five-Year Plan and Prospects for the 15th Five-Year Plan [J]. *Price Theory and Practice*, 2025, (07): 76-82.
- [12] Zhuang Qinqin , Wu Bin, Hong Qunlian . Market-oriented green technology innovation system: theoretical connotation, practical exploration and promotion strategy [J]. *Economist*, 2020, (11): 29-38.
- [13] Tingting B, Yong Q, Zihao L, et al. Digital economy, industrial transformation and upgrading, and spatial transfer of carbon emissions: The paths for low-carbon transformation of Chinese cities. [J]. *Journal of environmental management*, 2023, 344118528-118528.
- [14] Yang J, Lv X, Xu X , et al.Heterogeneous treatment effects of digital transformation on firms' innovation: Based on BART method[J].*Pacific -Basin Finance Journal*,2024,85102372-.
- [15] Chen Jianxing, Pan Shuang. Digital infrastructure empowers enterprise digitalization: An examination based on the perspective of digital technology innovation [J]. *Statistics and Decision*, 2024, 40(21):173-178.