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Research on the Impact of Digital-Real Industrial Technology Integration on the Development of New Quality Productive Forces in Enterprises

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Abstract

This study, based on data from 2015-2024 regarding digital-real industrial technology integration and samples of new quality productive forces in Shanghai and Shenzhen A-share listed enterprises, systematically examines the impact effects, influencing mechanisms, and heterogeneity characteristics of digital-real industrial technology integration on the development of new quality productive forces in enterprises. The research finds that digital-real industrial technology integration can significantly promote the development of new quality productive forces in enterprises; this impact is primarily achieved through three mechanism pathways: alleviating corporate financing constraints, enhancing innovation efficiency, and improving operational efficiency. Heterogeneity tests further reveal that the influence of digital-real industrial technology integration on the development of new quality productive forces in enterprises exhibits distinct differences at the enterprise, regional, and industry levels. At the enterprise level, technology-intensive, labor-intensive, and high-profit enterprises are more likely to foster the development of new quality productive forces through digital-real industrial technology integration. At the regional level, enterprises in the southern region and economically underdeveloped areas derive greater benefits from digital-real industrial technology integration. At the industry level, enterprises in high-tech sectors and those with high degrees of monopoly are better positioned to achieve the development of new quality productive forces through digital-real industrial technology integration. The study demonstrates that digital-real integration can promote the development of new quality productive forces in enterprises by alleviating financing constraints and elevating innovation and operational efficiency, while exhibiting heterogeneity effects at the enterprise, regional, and industry levels. These findings expand the theoretical connotations of the digital economy and high-quality development, providing empirical evidence and decision-making references for enterprises' differentiated transformations, governments' targeted policies, and optimized resource allocation.

Keywords

digital-real industrial technology integration, new quality productive forces in enterprises, financing constraints, innovation efficiency, operational efficiency

1. Introduction

As the core driving force leading the new round of scientific and technological revolution and industrial transformation, the integration of digital and real economies (digital-real integration) has been elevated to a strategic height in national development. The "14th Five-Year Plan for Digital Economy Development" explicitly proposes to take the deep integration of digital technology and the real economy as the main line, empowering the upgrading and transformation of traditional industries. At the macro level, digital-real integration is not only a strategic choice for building new national competitive advantages but also a key pathway for promoting qualitative improvements in the economy and reasonable quantitative growth. In 2024, China's digital economy scale exceeded 50 trillion yuan, accounting for over 40% of GDP, with its penetration and reshaping effects on the real economy becoming increasingly prominent, serving as a new engine driving high-quality development. However, under the dual pressures of deep adjustments in the global industrial chain and the transformation of domestic development models, how to deepen digital-real integration to address the structural contradictions in the development of the real economy has become a major practical issue that urgently needs resolution (Li and Liu, 2020).

In the new situation, accelerating the development of digital-real integration is a key link and driving engine for promoting industrial structure upgrading (Liu, 2025b). The essence of digital-real integration lies in reconstructing the models and pathways of value creation in the real economy through the drive of data elements and the empowerment of digital technologies. From the micro perspective of enterprises, digital-real integration is profoundly reshaping enterprises' core competitiveness by promoting the intelligence of production processes, the networking of organizational structures, and the innovation of business models, making it an inevitable choice for driving economic quality improvement and efficiency enhancement as well as building a modern economic system (Wu and Meng, 2025). With the rapid iteration of digital technologies, digital transformation has become a critical choice for enterprise survival and development (Qu and Li, 2025); however, current integration practices at the enterprise level generally face transformation pains: traditional constraints such as path dependence, data silos, and high sunk costs, as well as new challenges like rapid technological iteration, shortages of compound talents, and security and privacy issues. Exploring a path that can effectively unleash the value of integration and convert it into sustainable growth momentum is a focal point of common concern in theory and practice.

The concept and practical guidance of new quality productive forces have emerged in this context, with its core connotation being innovation-driven by scientific and technological innovation, breaking away from traditional growth paths to achieve a qualitative leap in total factor productivity. Existing studies have preliminarily revealed the positive impacts of digital technologies on enterprise innovation (Xie, 2025) and efficiency (Zhao, 2023), but the systemic project of "integration" lacks in-depth mechanistic analysis and solid micro-level evidence regarding how it specifically drives enterprises to form the intrinsic logic chain of "new quality." In particular, the heterogeneity effects of digital-real integration under different ownership natures, industry attributes, and regional environments, and how its effects are realized through specific pathways such as alleviating financing constraints (Xiang and Zhang, 2025) and optimizing resource allocation, all await rigorous empirical testing.

Based on this, this paper uses Shanghai and Shenzhen A-share listed enterprises from 2015 to 2024 as samples and comprehensively employs fixed effects models, instrumental variable methods, and propensity score matching methods to systematically test the impact effects, influencing mechanisms, and heterogeneity characteristics of enterprise digital-real industrial technology integration data on the development of new quality productive forces in enterprises. The study focuses on answering the following questions: How does digital-real industrial technology integration promote the development of new quality productive forces in enterprises? Are there intrinsic influencing mechanisms such as financing constraints, innovation efficiency, and operational efficiency? Does its impact effect exhibit differences at the enterprise, regional, and industry levels? Specifically, at the enterprise level, this study considers enterprise type and profitability; at the regional level, it considers north-south differences and economic development levels; at the industry level, it considers whether it is a high-tech industry and the degree of monopoly.

Existing literature mostly discusses the impacts of the digital economy on regional economic growth and industrial structure upgrading, but lacks in-depth and systematic micro-level evidence on how digital-real integration at the enterprise level specifically transforms into new quality productive forces. Compared to existing literature, the main marginal contributions of this paper are as follows: First, in terms of research perspective, this paper systematically examines the impact of digital-real integration on new quality productive forces from the micro enterprise level, supplementing the deficiencies in existing studies that mostly focus on macro or industry perspectives. Second, in terms of transmission mechanisms, based on listed company data, this paper reveals the micro transmission mechanisms from digital-real integration to new quality productive forces in terms of financing constraints, innovation efficiency, and operational efficiency, providing a new analytical layer for understanding the micro realization of macro strategies. Third, in terms of heterogeneity analysis, this paper not only tests differences in enterprise characteristics but also innovatively enters from multi-dimensional contexts such as regions and industries, revealing the complex boundary conditions of digital-real integration effects.

2. Theoretical Analysis and Research Hypotheses

2.1 Digital-Real Industrial Technology Integration and Enterprise New Quality Productive Forces

Digital-real industrial technology integration, namely the deep integration of digital technology and the real economy, represents the core direction of the evolution of productive forces and technological innovation at present (Pei et al., 2025). New quality productive forces emphasize the recombination and efficiency enhancement of production factors driven by scientific and technological innovation, with the core lying in breaking away from traditional factor input-driven paths to achieve a qualitative improvement in total factor productivity. From the perspective of "technology-strategy" (Zhou et al., 2025). synergistic evolution, the drive of digital-real integration on new quality productive forces transcends the instrumental cognition of traditional technology empowerment, manifesting as a systematic synergistic process of technological change, strategic integration, shaping new production factors, and organizational capabilities.

First, digital-real integration provides templates and tools for the nurturing of new quality productive forces. Digital technologies such as artificial intelligence, big data, cloud computing, and the Internet of Things not only improve existing production processes by optimizing information processing, reducing transaction costs, and enhancing resource allocation efficiency, but more crucially, they can engender entirely new products, services, business forms, and even business models, thereby creating new sources of market value and growth (Xu and Li, 2025). This lays a new technological foundation for new quality productive forces.

Second, strategic management theory posits that an enterprise's sustained competitive advantage stems from the construction of its resources and dynamic capabilities (Yang et al., 2025). Digital-real integration requires enterprises to undergo profound strategic changes, necessitating the redefinition of their value propositions, the construction of data-flow-centered decision-making systems, and the cultivation of organizational cultures, talent structures, and governance models that match the digital era (Wen and Li, 2025). This process internalizes external technological opportunities into the enterprise's unique strategies and organizational capabilities. Technology alone without adaptive strategies cannot form effective productive forces; strategies alone without underlying technological support render the "newness" and "quality" of productive forces unattainable.

Furthermore, digital-real integration, through the synergy of "technology-strategy," drives a profound transformation in the logic of value creation, which directly corresponds to the core characteristics of efficiency and quality in new quality productive forces (Liu, 2024). It enables enterprises to serve broader markets at lower marginal costs and meet diversified demands with greater precision, thereby achieving qualitative improvements (Wu and Du, 2024). This shift in the logic of value creation is the inevitable outcome of enterprises pursuing greater efficiency and higher quality, and it is a concrete manifestation of new quality productive forces at the micro level of value creation.

Finally, the "technology-strategy" synergistic perspective emphasizes environmental adaptability. The depth and breadth of digital-real integration, as well as its efficiency in transforming into new quality productive forces, are jointly influenced by external institutional environments, industrial ecosystems, and internal management cognitions. This explains why, under the same technological conditions, transformation outcomes exhibit heterogeneity across different enterprises (Guo et al., 2025). Those enterprises that can proactively formulate digital strategies, firmly promote organizational changes, and effectively absorb and utilize digital technologies are better positioned to convert the potential of digital-real integration into new quality productive forces.

Based on the above theoretical analysis, this paper proposes the following research hypothesis:

H1: Digital-real industrial technology integration can significantly promote the development of new quality productive forces in enterprises.

2.2 Digital-Real Industrial Technology Integration, Financing Constraints, and Enterprise New Quality Productive Forces

Financing constraints are a key bottleneck that restricts enterprise investment and innovation, thereby hindering productivity enhancement. Digital-real integration can effectively alleviate corporate financing constraints through two pathways—information mechanisms and asset mechanisms—thereby providing the necessary financial resources for the development of new quality productive forces (Yi et al., 2025).

On one hand, digital-real integration alleviates financing constraints caused by information asymmetry by enhancing enterprise information transparency and quality, creating more favorable financing conditions for investments in new quality productive forces. According to information asymmetry theory (Liu et al., 2025), the information disparity between external investors and internals is the root cause of high financing costs. Digital-real integration, particularly the digitization and intelligence of enterprise operations, enables real-time recording, tracking, and analysis of data across production, sales, inventory, and management links. This not only facilitates internal management but, more importantly, allows verifiable data—such as supply chain data, IoT device operation data, and user profile data (Liu, 2025a)—to be transmitted to external investors in a credible manner, significantly reducing the opacity of enterprise operations (Liu et al., 2024).

The alleviation of financing constraints primarily drives the development of new quality productive forces through two mechanisms: enhancing long-term investment capabilities and optimizing resource allocation structures. First, the alleviation of financing constraints directly strengthens enterprises' ability to engage in long-term strategic investments. The nurturing of new quality productive forces relies on frontier technology R&D, high-end talent acquisition, and advanced equipment procurement, which are characterized by long cycles, high risks, and uncertain short-term returns (Xiang and Zhang, 2025). Adequate financial support enables enterprises to overcome investment thresholds, pursue exploratory and disruptive innovations, and avoid interrupting critical R&D processes due to short-term financial pressures, thereby laying the material foundation for technological breakthroughs. Second, alleviating financing constraints helps optimize enterprises' resource allocation structures (Song et al., 2024). When internal cash flows are ample or external financing costs decrease, enterprises are more inclined to allocate funds to high-value-added, high-tech-content innovation activities rather than sustaining inefficient traditional operations.

Based on the above theoretical analysis, this paper proposes the following research hypothesis:

H2: Digital-real industrial technology integration indirectly promotes the development of new quality productive forces in enterprises by alleviating corporate financing constraints.

2.3 Digital-Real Industrial Technology Integration, Enterprise Innovation, and Enterprise New Quality Productive Forces

Innovation is the fundamental source of new quality productive forces. Digital-real integration empowers enterprise innovation activities comprehensively by reshaping the processes and elements of enterprise innovation, thereby directly driving the development of new quality productive forces. From the perspective of innovation processes and knowledge management (Zhou et al., 2025), its impact is profound and systematic.

First, digital-real integration greatly optimizes the processes and efficiency of enterprise innovation. Digital tools significantly shorten the cycles from conceptual design and functional testing to process optimization, while substantially reducing trial-and-error costs. This transforms enterprise innovation from a relatively closed process into an open, agile, and human-machine collaborative one, continuously stimulating the innovation capabilities of market entities in areas such as product marketing, creative design, and intelligent manufacturing (Pei et al., 2025), thereby significantly enhancing productivity. Second, digital-real integration expands the key elements and knowledge base of enterprise innovation, greatly extending the knowledge boundaries of enterprises, so that innovation no longer relies solely on the wisdom of internal R&D departments but can integrate global innovation networks (Yang et al., 2025).

The enhancement of innovation efficiency primarily promotes the leap of new quality productive forces through three dimensions: accelerating technological iteration, optimizing innovation ecosystems, and reshaping value creation logic (Xie, 2025). An efficient innovation system significantly accelerates the speed of technological iteration and knowledge diffusion (Zhou et al., 2025). Second, improvements in innovation efficiency optimize the internal and external innovation ecosystems of enterprises. Internally, cross-departmental collaboration becomes smoother, forming organizational capabilities that support complex innovations; externally, digital platforms enable more effective integration of innovation resources, achieving open innovation. Finally, high-efficiency innovation profoundly reshapes the value creation logic of enterprises—from pursuing economies of scale to network effects and personalized customization, and from providing standardized products to “products + services + experiences.” Therefore, strengthening enterprise innovation is a direct and critical pathway from digital-real integration to new quality productive forces.

Based on the above theoretical analysis, this paper proposes the following research hypothesis:

H3: Digital-real industrial technology integration indirectly promotes the development of new quality productive forces in enterprises by enhancing enterprise innovation efficiency.

2.4 Digital-Real Industrial Technology Integration, Operational Efficiency, and Enterprise New Quality Productive Forces

Operational efficiency is the foundational capability of enterprises to convert inputs into outputs, and it is the most direct micro-level manifestation of the “high-efficiency” characteristic of new quality productive forces (He et al., 2025). Digital-real integration comprehensively reshapes value creation processes by achieving precision and intelligence in enterprise operations, serving as the core means to enhance operational efficiency and thereby solidify the foundation of new quality productive forces. From the perspective of process reengineering and value networks, its enhancement effect is comprehensive.

Digital-real integration reshapes external supply chains and value chains (Zhang et al., 2025, Zhang et al., 2024), building efficient collaborative ecosystem networks. Through digital platforms, enterprises can achieve real-time sharing and automatic coordination of orders, inventory, and logistics information with suppliers, distributors, and logistics providers, realizing full visibility in the supply chain. This significantly reduces inventory levels, shortens delivery cycles, and improves the efficiency and resilience of the entire value chain. At the same time, enterprises can directly engage with end consumers via platforms, conducting precise marketing and personalized services based on data analysis to enhance customer satisfaction and optimize “market-end” operational efficiency.

The comprehensive enhancement of operational efficiency directly constitutes the foundation of “high efficiency” in new quality productive forces (Zhu et al., 2025). Improvements in operational efficiency are directly reflected in the intensive growth of total factor productivity. Through intelligent transformation of production processes, precise collaboration in supply chains, and lean management, enterprises systematically reduce energy consumption, material consumption, and time losses, achieving higher output quality and greater output quantities under the same factor inputs. New quality productive forces require obtaining more and better outputs with fewer resource inputs (Wu and Du, 2024). Digital-real integration systematically reduces various frictions in enterprise operations by optimizing internal processes and collaborating external networks, thereby enhancing total factor productivity. Therefore, the elevation of operational efficiency transforms digital-real integration into enterprises’ foundational competitiveness, serving as the efficiency cornerstone supporting the “high” and “new” aspects of new quality productive forces.

Based on the above theoretical analysis, this paper proposes the following research hypothesis:

H4: Digital-real industrial technology integration indirectly promotes the development of new quality productive forces in enterprises by enhancing enterprise operational efficiency.

3. Research Design

3.1 Sample Selection and Data Sources

This paper uses data from Shanghai and Shenzhen A-share listed enterprises in China as the research sample to empirically examine the impact of digital-real industrial technology integration on enterprise new quality productive forces. The data mainly include listed enterprises' annual reports, financial data, invention patent data, etc. Invention patent application data are sourced from the National Patent Database; enterprise new quality productive forces data are obtained from the CSMAR database and through text analysis of listed enterprises' annual reports; the remaining enterprise micro-level data are all from the CSMAR database. Under the premise of ensuring data stability and availability, the research period is determined to be 2015-2024, primarily based on the following considerations: First, this time span fully covers the national strategic cycle from "Made in China 2025" to the "14th Five-Year Plan," which is a critical decade for the evolution of digital-real integration from strategic proposal to deepened application, facilitating the observation of policy dynamic effects. Second, this decade is also a key stage in the maturation and widespread adoption of digital technologies, profoundly reshaping the real economy, providing an ideal window for examining the micro effects of digital-real integration. To ensure the standardization and validity of the data, this paper performs the following treatments: (1) Exclude samples from the financial industry; (2) Exclude enterprises that were in ST status or delisted during the sample period; (3) Exclude samples with missing key variables, and apply 1% two-tailed truncation to continuous variables. After processing, a total of 17,801 enterprise-year observations are obtained.

3.2 Variable Definitions

(1) Explained Variable. To construct the measurement indicator for enterprise new quality productive forces (NPRO), this paper refers to the research of Li et al. (2024) and Song et al. (2024), based on the two-element theory of productive forces, and considering the role and value of the labor object in the production process. Based on data availability, adjustments and comprehensiveness are made to its evaluation indicators to construct the enterprise new quality productive forces evaluation indicator system as shown in Table 1. Then, the entropy method is used to calculate the "new quality productive forces" variable.

Table 1: Enterprise New Quality Productive Forces Evaluation Indicator System

Primary Indicator	Secondary Indicator	Tertiary Indicator	Calculation Method	Weight/%
New Quality Laborers	Employee Quality	Proportion of R&D Personnel	(Number of R&D personnel / Number of employees) × 100	12.985
		Proportion of Highly Educated Personnel	(Number of postgraduates and above / Number of employees) × 100	8.855
	Management Quality	Executive Green Awareness	ln (Word frequency of green development keywords in annual report + 1)	6.320
		Management Overseas Background	1 if any executive has overseas background, otherwise 0	6.617
New Quality Labor Objects	Ecological Environment	Environmental Governance Score	E indicator from Huazheng ESG rating, with 9 levels assigned values 1–9	7.929
	Future Development	Proportion of Fixed Assets	(Fixed assets / Total assets) × 100	2.732
		Capital Accumulation Rate	(Increase in owners' equity for the current year / Owners' equity at the beginning of the year) × 100	1.124
New Quality	Technological Labor Materials	Innovation Level	ln (Number of authorized patents + 1)	21.810

Primary Indicator	Secondary Indicator	Tertiary Indicator	Calculation Method	Weight/%
Labor Materials	Digital Materials	Degree of Digitalization	ln (Word frequency of digitalization keywords in annual report + 1)	4.620
		Proportion of Intangible Assets	(Intangible assets / Total assets) × 100	4.100
	Green Labor Materials	Green Technology Level	ln (Number of authorized green patents + 1)	9.960
		Proportion of Green Patents	(Number of authorized green patents / Number of authorized patents) × 100	12.950

(2) Explanatory Variable. To construct the measurement indicator for digital-real industrial technology integration (CEDRT), this paper refers to the research of Guo et al. (2025), using an analysis method based on patent citation information to capture the flow characteristics of digital industry knowledge in the technological innovation of the real industry, and thereby assess enterprises' digital-real industrial technology integration behaviors. The selection method for the digital-real industrial technology integration variable in this study is as follows: If the IPC main classification number of a certain patent belongs to non-digital technology, but at least one of the cited patents belongs to digital technology, then this patent is regarded as one instance of an enterprise's digital-real technology integration behavior. To quantify the enterprise's behavior in terms of digital-real technology integration, the above-defined patent integration behaviors are aggregated at the annual level to obtain the number of digital-real industrial technology integrations for each enterprise in each year. By adding 1 to this number and taking the natural logarithm, the measurement indicator for enterprise digital-real industrial technology integration is constructed.

Mechanism Variables. To deeply explore the pathways through which digital-real integration affects the development of enterprise new quality productive forces, this paper sets mechanism variables from three aspects: financing constraints, innovation efficiency, and operational efficiency.

First, financing constraints (FC). Referring to the research of Xiang and Zhang (2025), this paper adopts the FC index as the measurement indicator for financing constraints, with data sourced from the CSMAR database. The FC index measurement method is as follows:

$$Investment\ Expenditure = \beta_0 + \beta_1 \times \mathrm{Tobin}Q + \beta_2 \times (Cash\ Flow/Capital\ Stock) + control + \varepsilon$$

The value of the FC index is reflected by the coefficients in the regression model β_2. This index comprehensively reflects the degree of difficulty faced by enterprises in external financing; a larger value indicates more severe financing constraints for the enterprise.

Second, innovation efficiency (Innovation). Referring to the research of Li and Zhang (2025), this paper follows the idea of innovation input-output conversion and measures it using the ratio of the natural logarithm of the number of patent applications in the current year plus 1 to the natural logarithm of R&D expenditure plus 1. A higher ratio represents higher enterprise innovation efficiency.

Third, operational efficiency (ATO). Referring to the research of Zhang and Zhang (2025), this paper uses total asset turnover (ATO) to measure enterprise operational efficiency, which is the ratio of operating revenue to average total assets. This indicator effectively reflects the management quality and operational efficiency of all enterprise assets.

(4) Control Variables. To control for the influence of potential factors, this paper refers to relevant research and selects control variables at the enterprise level, including asset-liability ratio, net profit margin on total assets, proportion of independent directors, Tobin's Q value, years since listing, and whether the enterprise is loss-making.

Specific variable definitions are shown in Table 2.

Table 2: Variable Definitions

Variable Type	Variable Symbol	Variable Name	Variable Definition
Explained Variable	NPRO	Enterprise New Quality Productive Forces	Comprehensive indicator calculated using the entropy method
Explanatory Variable	CEDRT	Digital-Real Industrial Technology Integration	ln (Enterprise's digital-real technology integration behaviors + 1)
Mechanism Variable	FC	Financing Constraints	FC Index
	Innovation	Innovation Efficiency	ln (Number of enterprise patent applications in the current year + 1) / ln (Enterprise R&D expenditure + 1)
	ATO	Operational Efficiency	Operating Revenue / Average Total Assets
Control Variable	Lev	Asset-Liability Ratio	Total Liabilities / Total Assets
	ROA	Net Profit Margin on Total Assets	Net Profit / Average Total Assets
	Indep	Proportion of Independent Directors	Independent Directors / Total Number of Directors
	TobinQ	Tobin's Q Value	Market Value of the Enterprise / Replacement Cost of Enterprise Assets
	ListAge	Years Since Listing	ln (Current Year - Listing Year + 1)
	Loss	Whether Loss-Making	1 if net profit in the current year < 0, otherwise 0

3.3 Model Construction

3.3.1 Baseline Regression Model

To examine the impact of digital-real industrial technology integration on enterprise new quality productive forces, the baseline regression model is constructed as follows:

$$NPRO_{i,t} = \alpha_0 + \alpha_1 CEDRT_{i,t} + \alpha_2 controls_{i,t} + \delta_{Year} + \eta_{Firm} + \varepsilon_{i,t} \tag{1}$$

Where *i* and *t* represent the enterprise and year, respectively; *NPRO* represents enterprise new quality productive forces; *CEDRT* represents digital-real industrial technology integration; *controls* represents control variables; δ_{Year} represents year fixed effects; η_{Firm} represents firm fixed effects; and ε represents the random disturbance term.

3.3.2 Mechanism Test Model

According to the theoretical analysis above, financing constraints, innovation efficiency, and operational efficiency play mediating roles in the process of digital-real industrial technology integration promoting the development of enterprise new quality productive forces. Referring to the research of Li et al. (2024) and Li and Zhang (2025), this paper constructs the following mechanism test models:

$$FC_{i,t} = \alpha_0 + \alpha_1 CEDRT_{i,t} + \alpha_2 controls_{i,t} + \delta_{Year} + \eta_{Firm} + \varepsilon_{i,t} \tag{2}$$

$$Innovation_{i,t} = \alpha_0 + \alpha_1 NQP_{i,t} + \alpha_2 controls_{i,t} + \delta_{Year} + \eta_{Firm} + \varepsilon_{i,t} \tag{3}$$

$$ATO_{i,t} = \alpha_0 + \alpha_1 NQP_{i,t} + \alpha_2 controls_{i,t} + \delta_{Year} + \eta_{Firm} + \varepsilon_{i,t} \tag{4}$$

Where *i* and *t* represent the enterprise and year, respectively; *FC* represents financing constraints, *Innovation* represents innovation efficiency, and ATO represents operational efficiency; the other variables are as defined above.

4. Empirical Analysis

4.1 Descriptive Statistics

The descriptive statistics of the main variables are shown in Table 3. The mean value of enterprise new quality productive forces is 0.1760, the median is 0.1590, the minimum is 0.0327, and the maximum is 0.3800, indicating significant differences in the development levels of new quality productive forces among the sample enterprises. The mean value of enterprise digital-real industrial technology integration is 1.0400, the standard deviation is 0.6060, the minimum is 0.0327, and the maximum is 0.3800, showing uneven distribution in the depth and breadth of digital-real industrial technology integration among the sample enterprises, with obvious differences.

Table 3 Descriptive Statistics of Variables

Variable	Observations	Minimum	Maximum	Mean	Median	Standard Deviation
NPRO	17801	0.0327	0.3800	0.1760	0.1590	0.0873
CEDRT	17801	0.6930	3.6890	1.0400	0.6930	0.6060
Lev	17801	0.0941	0.8690	0.4920	0.5070	0.1840
ROA	17801	-0.1750	0.2030	0.0432	0.0391	0.0554
Indep	17801	33.3300	57.1400	38.2300	36.3600	6.0080
TobinQ	17801	0.8270	6.7570	1.8160	1.4690	1.0740
ListAge	17801	0.0000	3.3670	2.3340	2.4850	0.8120
Loss	17801	0.0000	1.0000	0.1070	0.0000	0.3090

4.2 Baseline Regression

To examine the impact of digital-real integration on enterprise new quality productive forces, this paper conducts baseline regression analysis, with results shown in Table 4.

Column (1) presents the standalone regression results of enterprise digital-real industrial technology integration on enterprise new quality productive forces without including control variables. The results show that the regression coefficient of CEDRT is 0.0027 and is significantly positive at the 1% level, preliminarily indicating that digital-real integration has a positive promotional effect on the development of enterprise new quality productive forces.

Column (2) adds a series of enterprise-level control variables to Column (1). The results show that, after controlling for the influence of other factors, the coefficient of the core explanatory variable CEDRT is 0.0029, remaining positive and significant at the 1% statistical level. This indicates that digital-real integration can significantly drive the development of enterprise new quality productive forces, thus Hypothesis 1 is supported. From an economic significance perspective, the coefficient of CEDRT suggests that for every unit increase in the level of digital-real integration, the level of enterprise new quality productive forces will increase by approximately 0.29% on average.

Table 4: Baseline Regression Results

	(1)	(2)
Variable	NPRO	NPRO
CEDRT	0.0027***	0.0029***
	(2.8022)	(2.9498)
Lev		0.0052

		(0.7707)
ROA		-0.0838***
		(-6.0025)
Indep		0.0006***
		(4.8551)
TobinQ		0.0014*
		(1.8998)
ListAge		0.0024
		(0.9855)
Loss		-0.0057***
		(-2.8653)
Constant	0.1784***	0.1489***
	(152.3336)	(18.7675)
Observations	12,817	12,817
R-squared	0.8470	0.8490
Adj. R2	0.7850	0.7850

*Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.*

4.3 Influencing Mechanisms

The baseline regression confirms the overall promotional effect of digital-real integration on enterprise new quality productive forces. To further reveal its intrinsic pathways, this paper, based on theoretical analysis, examines whether financing constraints, innovation efficiency, and operational efficiency play mediating roles therein.

4.3.1 Financing Constraint Alleviation Mechanism

Columns (1) and (2) of Table 5 report the mechanism test results for the influence of financing constraints (FC). Column (1) shows that the coefficient of the core explanatory variable CEDRT on the mechanism variable FC is significantly negative at the 1% level. This indicates that digital-real integration can significantly reduce the level of enterprise financing constraints. Column (2) shows that after incorporating the mechanism variable FC, the coefficient of FC is significantly negative at the 1% level, while the coefficient of CEDRT remains significantly positive at the 1% level. The results suggest that the alleviation of financing constraints is an important mechanism through which digital-real integration drives the development of new quality productive forces. Economically, this implies that enterprises enhance information transparency and credit qualifications through digital transformation, thereby facilitating access to external financing and providing financial support for innovation activities and efficiency improvements.

4.3.2 Innovation Efficiency Enhancement Mechanism

Columns (3) and (4) report the mechanism test results for innovation efficiency. Column (3) shows that the coefficient of CEDRT on Innovation is significantly positive at the 1% level, indicating that digital-real integration can effectively enhance enterprise innovation efficiency. Column (4) shows that after controlling for CEDRT, the coefficient of innovation efficiency is significantly positive at the 1% level. The results indicate that innovation efficiency is an important mechanism through which digital-real integration drives the development of new quality productive forces. Economically, this means that digital technologies improve enterprise innovation output efficiency by optimizing R&D processes, promoting knowledge sharing, and accelerating technological iteration, thereby translating into substantive productivity advancements.

4.3.3 Operational Efficiency Enhancement Mechanism

Columns (5) and (6) report the mechanism effect test results for operational efficiency. Column (5) shows that the coefficient of CEDRT on ATO is significantly positive at the 1% level, indicating that digital-real integration can significantly improve enterprise operational efficiency. Column (6) shows that after controlling for CEDRT, the coefficient of operational efficiency is significantly positive at the 1% level. The results suggest that operational efficiency is another effective pathway through which digital-real integration influences new quality productive forces. Economically, this implies that digital technologies drive the development of new quality productive forces by optimizing production processes, strengthening supply chain collaboration, and achieving refined management, thereby reducing costs and increasing efficiency.

Table 5: Impact Mechanism Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	FC	FC	innovation	innovation	ATO	ATO
CEDRT	-0.0078***	-0.0063***	0.0079***	0.0079***	0.0136***	0.0123***
	(-3.4474)	(-3.3459)	(8.1510)	(8.2051)	(4.0273)	(3.9571)
Lev		-0.5336***		-0.0144**		0.3295***
		(-41.2361)		(-2.1422)		(15.2142)
ROA		0.1942***		-0.0049		1.4439***
		(7.2523)		(-0.3519)		(32.1574)
Indep		0.0004		0.0001		0.0015***
		(1.5166)		(0.9372)		(3.7862)
TobinQ		-0.0046***		0.0015**		0.0164***
		(-3.2496)		(2.0660)		(6.9134)
ListAge		-0.1453***		-0.0051**		-0.0747***
		(-31.5462)		(-2.1497)		(-9.7400)
Loss		0.0058		-0.0017		0.0191***
		(1.5284)		(-0.8613)		(2.9892)
Constant	0.2743***	0.8739***	0.1348***	0.1473***	0.6682***	0.5309***
	(101.0783)	(57.3492)	(115.7301)	(18.6740)	(164.0800)	(20.8158)
Observations	12,703	12,703	12,452	12,452	12,817	12,817
R-squared	0.9170	0.9430	0.8980	0.8980	0.8880	0.9050
Adj. R2	0.8650	0.8650	0.8650	0.8650	0.8650	0.8650

*Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.*

4.4 Endogeneity Tests

4.4.1 Instrumental Variable Method

This paper employs the instrumental variable method for endogeneity testing.

Instrumental Variable 1 (IV1): The one-period lag of digital-real industrial technology integration (L.CEDRT). Digital-real industrial technology integration typically exhibits time inertia, such as the accumulation of technological innovations and the continuity of innovation experiences. The one-period lag L.CEDRT is significantly positively correlated with the current CEDRT, satisfying the relevance requirement between the instrumental variable and the endogenous variable. There may be bidirectional causality between the current level of digital-real integration and enterprise new quality productive forces development. Using the one-period lag L.CEDRT, which precedes the explained variable in time, reduces the reverse influence of the current outcome variable on the explanatory variable and enhances exogeneity.

Instrumental Variable 2 (IV2): The mean value of digital-real integration among other enterprises in the same city and same industry in the same year. Enterprises in the same region and industry face similar industrial policies, digital infrastructure, and market environments, so their digital-real integration behaviors exhibit significant peer or cluster effects, making this instrumental variable relevant to a specific enterprise's digital-real integration level. However, the average behavior of other enterprises does not directly affect the focal enterprise's new quality productive forces; its influence can only be realized through impacting the focal enterprise's decisions, thus satisfying the exogeneity requirement.

This paper adopts the two-stage least squares (2SLS) method for estimation, with results shown in Table 6. Columns (1) and (3) are the first-stage regression results using IV1 and IV2 as instrumental variables, respectively, while Columns (2) and (4) are the corresponding second-stage regression results.

First, the first-stage regression results show that under both instrumental variable settings, the impact of the instrumental variables on the endogenous explanatory variable CEDRT is significantly positive at the 1% level. This strongly proves the extremely strong correlation between the instrumental variables and the endogenous variable, satisfying the instrumental variable relevance condition.

Second, the second-stage regression results show that after using each instrumental variable separately, the coefficient of the core explanatory variable CEDRT is significantly positive at the 1% level. Compared to the baseline OLS results, the 2SLS estimates yield larger coefficients, indicating that the baseline regression may have underestimated the true effect of digital-real integration due to endogeneity issues. After controlling for endogeneity, the positive promotional effect of digital-real integration on enterprise new quality productive forces remains robust, with the causal relationship being clearer.

Table 6: Instrumental Variable Method Results

	(1)	(2)	(3)	(4)
	first	second	first	second
Variable	CEDRT	NPRO	CEDRT	NPRO
LCEDRT	0.6890***			
	(86.7540)			
CEDRT_city_ind			0.5050***	
			(28.7050)	
CEDRT		0.0430***		0.1520***
		(22.2560)		(23.2800)
Lev	0.2450***	0.0460***	0.3300***	-0.0010
	(5.7200)	(6.3440)	(10.7500)	(-0.2190)
ROA	0.8120***	0.0820***	0.9490***	-0.0360
	(4.8410)	(2.9170)	(8.3170)	(-1.6050)
Indep	0.0010	-0.0000***	0.0020**	-0.0010***
	(0.8430)	(-2.9080)	(2.5950)	(-4.2030)

TobinQ	0.0010	0.0050***	-0.0150**	0.0050***
	(0.0750)	(4.1950)	(-2.9580)	(4.8060)
ListAge	0.0240**	0.0140***	0.0250***	0.0040***
	(2.3060)	(7.7520)	(3.7570)	(3.3540)
Loss	0.0010	-0.0110**	-0.0180	-0.0080*
	(0.0360)	(-2.3280)	(-0.9880)	(-2.3920)
Constant	-0.3690***	0.1690***	0.2560***	0.0080
	(-3.9510)	(10.8600)	(5.6620)	(0.8660)
Observations	6,606	6,606	16294	16294
R-squared	0.5640	0.1240	0.0840	0.0840
Adj. R2	0.5630	0.1220	0.0830	0.0830

*Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.*

4.4.2 Propensity Score Matching Method (PSM)

This paper uses the propensity score matching method to mitigate endogeneity issues arising from sample self-selection. The specific research design is as follows: First, the sample is divided into treatment and control groups based on the median of digital-real integration. Second, all control variables from the baseline regression are selected as covariates, and a Logit model is used to estimate the propensity scores for enterprises entering the treatment group. Finally, the nearest neighbor 1:1 matching without replacement is employed to match each treatment group enterprise with the most similar propensity score individual in the control group. After matching, a balanced panel dataset of 9,437 observations is obtained.

The regression results on the matched sample are shown in Table 7. After controlling for all variables, the coefficient of the core explanatory variable CEDRT is 0.0034, remaining significantly positive at the 1% level. Compared to the baseline regression results, the coefficient size and significance level are very close, with a slight increase. This result strongly indicates that after effectively alleviating endogeneity bias caused by sample self-selection, the positive driving effect of digital-real industrial technology integration on enterprise new quality productive forces remains robust, further supporting the establishment of research Hypothesis 1.

Table 7: Propensity Score Matching Results

	(1)	(2)
Variable	NPRO	NPRO
CEDRT	0.0031***	0.0033***
	(2.9303)	(3.0509)
Lev		0.0053
		(0.6468)
ROA		-0.0907***
		(-5.1833)
Indep		0.0006***
		(4.3860)
TobinQ		0.0014

		(1.5449)
ListAge		0.0016
		(0.5540)
Loss		-0.0070***
		(-2.8474)
Constant	0.1854***	0.1573***
	(129.0564)	(16.3144)
Observations	9,437	9,437
R-squared	0.8570	0.8590
Adj. R2	0.7980	0.7980

*Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.*

4.5 Robustness Tests

To further verify the reliability of the research conclusions, this study conducts multiple robustness tests, with results shown in Table 8:

First, replacing the explanatory variable. Referring to the research of Song et al. (2024), to test whether the results depend on the variable measurement method, Column (1) adopts a new digital-real integration measurement indicator (CEDRT2), referencing the digital-real integration measurement method of Huang and Gao (2023). The regression results show that the coefficient of CEDRT2 is 0.0017, significantly positive at the 5% level. The basic conclusion of positive significance remains unchanged, further supporting the robustness of the research hypotheses.

Second, changing fixed effects. The baseline regression mainly controls for year and firm fixed effects. To exclude the influence of more macro-level unobservable factors, Column (2) further controls for “province-year” joint fixed effects on the baseline model. The results show that the coefficient of the core explanatory variable digital-real integration is 0.0049, remaining significantly positive at the 1% level. This indicates that after controlling for macro factors that vary simultaneously with provinces and time, the positive promotional effect of digital-real integration on enterprise new quality productive forces remains robust.

Third, longer time span. Referring to the research of Zhao and Hong (2025), considering that the COVID-19 pandemic in 2020 may have caused structural shocks to enterprises and the macroeconomy, to avoid interference from this extreme exogenous event on the results, Column (3) adjusts the sample period to 2015-2019, excluding pandemic-era data. In this subsample, the coefficient of CEDRT is 0.0035 and remains significant at the 5% level. This result confirms that the positive effect of digital-real integration also exists in the pre-pandemic normal economic period, and the positive promotional effect on enterprise new quality productive forces remains robust.

Fourth, excluding municipalities directly under the central government. Referring to the research of Chen and He (2025), considering the special nature of municipalities directly under the central government (Beijing, Shanghai, Tianjin, Chongqing) in administrative levels, policy resources, and market environments, which may inappropriately influence the overall estimates, Column (4) reports the regression results after excluding samples from these municipalities. The results show that the coefficient of CEDRT is 0.0275, with a significance level of 1%. This indicates that the core conclusions of this paper are not driven by the special performance of municipalities, enhancing the universality of the conclusions.

Table 8: Robustness Test Results

	(1)	(2)	(3)	(4)

	Replace Explanatory Variable	Change Fixed Effects	Longer Time Span	Exclude Municipalities
Variable	NPRO	NPRO	NPRO	NPRO
CEDRT		0.0275***	0.0035**	0.0044***
		(30.0091)	(2.5755)	(4.1931)
CEDRT2	0.0017**			
	(2.5739)			
Lev	0.0226**	0.0502***	0.0025	0.0011
	(2.4595)	(13.8876)	(0.2535)	(0.1619)
ROA	-0.1280***	0.0914***	-0.0471**	-0.0852***
	(-6.6620)	(6.5896)	(-2.5073)	(-6.0019)
Indep	0.0007***	-0.0003***	0.0006***	0.0001
	(4.5040)	(-3.0508)	(3.4931)	(0.6026)
TobinQ	0.0024***	0.0013**	0.0030***	0.0015**
	(2.6493)	(2.0228)	(2.6685)	(1.9980)
ListAge	-0.0032	0.0053***	0.0020	0.0037
	(-1.0290)	(6.5374)	(0.5168)	(1.5014)
Loss	-0.0097***	-0.0083***	-0.0047*	-0.0061***
	(-3.4684)	(-3.7903)	(-1.7823)	(-2.9290)
Constant	0.1657***	0.1176***	0.1374***	0.1680***
	(16.4231)	(25.3348)	(11.6532)	(19.6716)
Observations	8,671	21,348	6,940	10,483
R-squared	0.8330	0.1600	0.8640	0.8640
Adj. R2	0.7640	0.1580	0.7910	0.8060

*Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.*

4.6 Heterogeneity Tests

Tables 9, 10, and 11 report the heterogeneity test results for the impact of digital-real industrial technology integration on the development of enterprise new quality productive forces from the enterprise, regional, and industry levels, respectively.

4.6.1 Enterprise Level

At the enterprise level, the sample is divided into technology-intensive, capital-intensive, and labor-intensive enterprises to examine how the effects of digital-real integration differ due to variations in core production factors; and divided into high-profit and low-profit groups based on the median return on assets (ROA) to test whether enterprises' financial resource endowments affect the implementation effects of digital-real integration.

The results in Column (1) show that in technology-intensive enterprises, the coefficient of digital-real integration is 0.0029 and significantly positive at the 1% level. The results in Column (2) show that the coefficient of CEDRT is 0.0049 but fails the significance test. The results in Column (3) show that in labor-intensive enterprises, the coefficient of CEDRT is 0.0055 and significant at the 10% level. This indicates that the empowerment effect of digital-real integration is most significant for technology-intensive enterprises. The reason is that for technology-intensive enterprises centered on innovation, digitalization can directly integrate into R&D and design processes, significantly enhancing innovation efficiency and achievement transformation, with the driving role being the most direct. For capital-intensive enterprises reliant on heavy equipment, digital transformation often requires deep retrofitting of production facilities, involving large investments and long cycles, with benefits emerging with obvious lags. For labor-intensive enterprises, the value of digital transformation lies in optimizing management processes to quickly achieve cost reductions and efficiency gains, thereby enhancing productivity. This conclusion provides clear empirical evidence for differentiated transformations of different types of enterprises.

The results in Column (4) show that for high-profit enterprises, the coefficient of digital-real integration is 0.0053 and highly significant at the 1% level. The results in Column (5) show that for low-profit enterprises, the coefficient of CEDRT is only 0.0003 and completely insignificant. This comparison clearly reveals the financing constraint issues faced by enterprises. Enterprises with strong profitability have greater capabilities and resources to invest in and implement digital-real integration strategies. Enterprises with weaker profitability may lack the funds to bear the high costs of digital transformation, or even if they invest, resource limitations may hinder deep integration, resulting in weak marginal effects of digital-real integration and difficulty in translating into significant improvements in new quality productive forces in the short term.

Table 9: Heterogeneity Test Results at the Enterprise Level

	(1)	(2)	(3)	(4)	(5)
	Technology-Intensive	Capital-Intensive	Labor-Intensive	High-Profit Enterprises	Low-Profit Enterprises
Variable	NPRO	NPRO	NPRO	NPRO	NPRO
CEDRT	0.0029***	0.0049	0.0055*	0.0053***	0.0003
	(2.7290)	(1.4425)	(1.7205)	(4.0094)	(0.2131)
Lev	0.0019	-0.0249	0.0130	0.0190*	0.0042
	(0.2346)	(-1.1663)	(0.7074)	(1.8062)	(0.3760)
ROA	-0.1011***	-0.0293	-0.0827**	-0.1051***	-0.0358
	(-6.2698)	(-0.6850)	(-2.1266)	(-3.9526)	(-1.4135)
Indep	-0.0003**	0.0001	0.0026***	-0.0001	0.0013***
	(-2.2616)	(0.2980)	(10.0239)	(-0.4432)	(7.3896)
TobinQ	0.0023***	-0.0039	0.0012	0.0029***	0.0013
	(2.8457)	(-1.5156)	(0.5024)	(3.1348)	(0.7602)
ListAge	0.0017	0.0035	-0.0064	-0.0049*	-0.0001
	(0.6686)	(0.4198)	(-0.7511)	(-1.7008)	(-0.0082)
Loss	-0.0075***	-0.0010	0.0023	-0.0170*	-0.0008
	(-3.2915)	(-0.1741)	(0.4058)	(-1.7316)	(-0.3125)
Constant	0.2022***	0.1571***	0.0411*	0.1926***	0.1217***
	(22.2976)	(5.5649)	(1.6573)	(17.4203)	(6.3107)
Observations	8,922	1,482	2,240	5,593	5,745
R-squared	0.8660	0.8040	0.7320	0.8800	0.8400

Adj. R2	0.7630	0.7630	0.7630	0.7630	0.7630

*Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.*

4.6.2 Regional Level

At the regional level, the sample is divided into two subsamples: the "northern region" north of the Qinling-Huaihe Line and the "southern region" south of it, to examine whether China's classic north-south economic geographical differentiation is reflected in the effects of digital-real integration; and divided into "economically developed" and "economically underdeveloped" groups based on the median GDP of each province to test whether the overall economic scale of the region constitutes an influencing condition.

The results in Column (1) show that in the northern region, the coefficient of CEDRT is -0.0017 and fails the significance test, indicating no statistically significant promotional effect of digital-real integration on enterprise new quality productive forces in the northern region. The results in Column (2) show that in the southern region, the coefficient of digital-real integration (CEDRT) is 0.0057 and highly significant at the 1% level, indicating a strong and significant driving effect on enterprise new quality productive forces (NPRO). The reason is that the southern region, dominated by private economy, export-oriented economy, and high-tech industries, has a vibrant innovation atmosphere and an industrial structure centered on electronics, information, and high-end manufacturing, enabling faster conversion of digital technologies into productive forces. In contrast, the northern region has a higher proportion of traditional heavy and chemical industries and resource-based industries, facing greater transformation difficulties and longer cycles.

The results in Column (3) show that in economically developed provinces, the coefficient of CEDRT is positive (0.0019) but fails the significance test. The results in Column (4) show that in provinces with relatively lower economic development levels, the coefficient of digital-real integration is 0.0046 and significant at the 1% level. This indicates that at the enterprise level in underdeveloped regions, digital-real integration is an effective pathway to enhance new quality productive forces. For regions with smaller GDP, the overall level of industrial digitization is generally lower. At this point, any degree of digital-real integration investment by enterprises may bring significant marginal improvements. In regions with larger GDP, digital infrastructure and industrial digitization levels are already high, and digital competition among enterprises is intense; thus, conventional digital-real integration investments may have become standard, with marginal benefits beginning to diminish.

Table 10: Heterogeneity Test Results at the Regional Level

	(1)	(2)	(3)	(4)
	Northern Region	Southern Region	Economically Developed	Economically Underdeveloped
Variable	NPRO	NPRO	NPRO	NPRO
CEDRT	-0.0017	0.0057***	0.0019	0.0046***
	(-0.9692)	(4.7485)	(1.3780)	(3.3684)
Lev	-0.0030	0.0019	0.0173*	-0.0141
	(-0.2152)	(0.2385)	(1.7024)	(-1.5130)
ROA	-0.1068***	-0.0695***	-0.0743***	-0.0930***
	(-3.5997)	(-4.2303)	(-3.5631)	(-4.7869)
Indep	0.0012***	0.0002	0.0006***	0.0004**
	(6.1608)	(1.1567)	(3.9090)	(2.0072)
TobinQ	0.0038**	0.0006	0.0004	0.0024**
	(2.2412)	(0.7291)	(0.3504)	(2.3496)

ListAge	0.0025	0.0030	0.0032	0.0002
	(0.4016)	(1.1139)	(0.9425)	(0.0586)
Loss	-0.0027	-0.0053**	-0.0088***	-0.0030
	(-0.6894)	(-2.2189)	(-2.9755)	(-1.0753)
Constant	0.1256***	0.1673***	0.1415***	0.1681***
	(6.5015)	(17.8089)	(12.8706)	(13.9308)
Observations	3,847	8,203	6,538	5,982
R-squared	0.8210	0.8650	0.8430	0.8590
Adj. R2	0.7980	0.7980	0.7980	0.7980

*Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.*

4.6.3 Industry Level

The sample is divided into high-tech and non-high-tech industries to examine how the effects of digital-real integration differ due to variations in industry technology intensity; and divided into “high monopoly degree” and “low monopoly degree” groups using the median Lerner Index as the measurement indicator for monopoly degree (Xu and Li, 2025).

The results in Column (1) show that in high-tech industries, the coefficient of digital-real integration is 0.0041 and highly significant at the 1% level. The results in Column (2) show that in non-high-tech industries, the coefficient of CEDRT is 0.0008 and fails the significance test. This significant contrast illustrates that the promotional effect of digital-real integration exhibits obvious technological preferences. For non-high-tech industries, with relatively traditional business models and higher thresholds for digital technology applications, the average effect is insignificant. The core competitiveness of high-tech enterprises lies in R&D innovation and technological iteration; digital-real integration can directly empower their R&D design, production processes, and business models, greatly enhancing innovation efficiency and thus having the most significant promotional effect on new quality productive forces.

The results in Column (3) show that in industries with high monopoly degrees, the coefficient of digital-real integration is 0.0054 and highly significant at the 1% level. The results in Column (4) show that in highly competitive industries, the coefficient of CEDRT is 0.0004 and insignificant. This indicates that enterprises with certain market power benefit more from digital-real integration. The reason is that the excess profits brought by monopoly status provide ample internal financial support for enterprises to undergo digital transformation, and to maintain their market positions and competitive advantages, these enterprises have stronger incentives to pursue digital-real industrial technology integration. For enterprises with low monopoly degrees, intense market competition compresses profits to extremely low levels, with most resources needed for daily operations and coping with competition, lacking sufficient internal funds for the long-cycle investments required in digital transformation.

Table 11: Heterogeneity Test Results at the Industry Level

	(1)	(2)	(3)	(4)
	High-tech Industry	Non-High-tech Industry	High Monopoly Degree	Low Monopoly Degree
Variable	NPRO	NPRO	NPRO	NPRO
CEDRT	0.0041***	0.0008	0.0054***	0.0004
	(3.4245)	(0.5016)	(3.4458)	(0.2667)
Lev	0.0026	0.0047	0.0262**	0.0040
	(0.2777)	(0.4616)	(2.3655)	(0.3893)

ROA	-0.0862***	-0.0780***	-0.0625***	-0.0964***
	(-4.6430)	(-3.5656)	(-2.7842)	(-4.3555)
Indep	0.0001	0.0010***	-0.0006***	0.0016***
	(0.7545)	(5.5938)	(-2.7552)	(9.8260)
TobinQ	0.0019**	0.0014	0.0003	0.0021*
	(2.0697)	(1.0864)	(0.2457)	(1.6833)
ListAge	0.0028	-0.0022	0.0083**	-0.0089**
	(0.9253)	(-0.5702)	(2.2813)	(-2.1443)
Loss	-0.0096***	-0.0004	-0.0006	-0.0081**
	(-3.6782)	(-0.1400)	(-0.1763)	(-2.5421)
Constant	0.1810***	0.1258***	0.1769***	0.1339***
	(16.6571)	(10.3770)	(13.7899)	(10.1716)
Observations	7,256	5,470	5,611	5,496
R-squared	0.8590	0.8180	0.8540	0.8730
Adj. R2	0.8080	0.8080	0.8080	0.8080

*Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.*

5. Conclusion and Implications

Based on panel data from Shanghai and Shenzhen A-share listed enterprises from 2015 to 2024, this paper systematically examines the impact effects, influencing mechanisms, endogeneity tests, robustness tests, and heterogeneity analyses of enterprise digital-real industrial technology integration on the development of enterprise new quality productive forces. The research findings are as follows: (1) Digital-real industrial technology integration can significantly promote the development of enterprise new quality productive forces; (2) This impact is primarily achieved through three mechanism pathways: alleviating enterprise financing constraints, enhancing innovation efficiency, and improving operational efficiency; (3) Endogeneity tests and robustness tests further demonstrate that the significant effect of digital-real industrial technology integration in promoting the development of enterprise new quality productive forces is robust; (4) Heterogeneity tests reveal that the influence of digital-real industrial technology integration on the development of enterprise new quality productive forces exhibits distinct differences at the enterprise, regional, and industry levels. At the enterprise level, technology-intensive, labor-intensive, and high-profit enterprises are more likely to promote the development of new quality productive forces through digital-real industrial technology integration; at the regional level, enterprises in the southern region and economically underdeveloped areas derive greater benefits from digital-real industrial technology integration; at the industry level, enterprises in high-tech sectors and those with high degrees of monopoly are better positioned to achieve the development of new quality productive forces through digital-real industrial technology integration.

Based on this study, this paper proposes the following three research implications:

First, at the strategic level, elevate digital-real integration to the core strategy for driving the development of new quality productive forces. This research confirms that digital-real integration can significantly drive the development of enterprise new quality productive forces. Therefore, governments at all levels should place the promotion of deep digital-real integration at the core of regional economic development strategies, fostering a macro environment conducive to digital transformation through top-level design, policy guidance, and infrastructure construction. For enterprises, it is essential to recognize from a strategic height that digital-real integration is not an optional elective but a mandatory course concerning future core competitiveness. Enterprises should formulate long-term digital transformation plans, particularly in key links such as R&D,

production, and supply chains, to drive the sustained growth of new quality productive forces.

Second, at the pathway level, focus on key mechanisms to address bottlenecks and difficulties in digital-real integration. On the financing side, governments should innovate financial support tools, developing specialized credit products for digital transformation, intellectual property pledge financing, etc., to broaden funding sources for enterprise transformations. Enterprises need to proactively optimize their financial structures, enhance credit levels, and actively leverage capital markets for support. On the innovation side, policies should encourage "industry-academia-research-application" collaboration and build industry-level digital innovation platforms. Enterprises should deeply integrate digital technologies into the full processes of R&D, design, and testing to drive innovation transformations. On the operational side, the focus lies in achieving refined production processes and rapid supply chain responses through intelligent retrofitting and process reengineering, ultimately attaining the core goals of cost reduction, efficiency enhancement, and quality improvement.

Third, at the implementation level, adhere to differentiated principles to achieve targeted policies and categorized advancement. The significant differences revealed by heterogeneity tests indicate that a one-size-fits-all promotion model is inefficient; it is necessary to uphold the differentiated principles of "tailoring to local conditions, to industries, and to enterprises." For enterprises, technology-intensive enterprises should boldly explore deep integration of frontier technologies and lead as innovation pioneers; labor-intensive enterprises should focus on resolving pain points such as labor shortages, cumbersome management, and low efficiency through digitalization; high-profit enterprises should leverage their funding advantages for strategic investments; while low-profit enterprises can start from low-investment, quick-return links and gradually deepen integration. For governments and regulatory authorities: Policies in the southern region should emphasize encouraging high-end breakthroughs and ecosystem building; northern regions and economically underdeveloped areas should focus on improving digital infrastructure, guiding local enterprises to take the first step through demonstration projects, subsidies, and other means. For high-tech and high-monopoly industries, encourage them to create benchmark cases and exert radiating and driving effects; for traditional and highly competitive industries, prioritize providing inclusive public service platforms for digital transformation to lower the entry thresholds for SMEs.

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Conflicts of Interest

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