The Impact of Digital Transformation on the New Productivity of Enterprises an Empirical Analysis of Industry Heterogeneity Differences

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Abstract. As China navigates a crucial stage of economic transition and industrial enhancement, its conventional growth paradigm faces increasing challenges in sustaining high-quality development. In this context, the concept of “new quality productivity” has gained significant attention. Digital transformation has become a pivotal driving force in supporting this evolution. However, empirical research on the firm-level impact of digital transformation on new quality productivity remains relatively scarce. This paper explores both the direct and mediating pathways through which digital transformation affects new quality productivity, particularly by advancing digital technologies and through investment in innovation, thereby offering valuable insights for both scholarship and practice. Drawing on panel data from A-share listed firms in China from 2015 to 2022, the analysis employs multiple regression models alongside mediation analysis to deliver a thorough evaluation. The findings highlight three main conclusions: (1) Digital transformation positively and significantly influences firms’ new quality productivity, evidenced by a regression coefficient of 0.002, which is statistically significant at the 1% level and economically relevant; (2) This impact is partially mediated through improvements in digital technology, with a supporting correlation coefficient of 0.041. However, the mediating role of innovation investment lacks statistical significance, suggesting firms still have opportunities to enhance both the effectiveness and alignment of such investments; (3) The heterogeneity analysis reveals that the influence of digital transformation is more pronounced in small and medium-sized enterprises, with a coefficient of 0.002, surpassing the 0.001 effect observed in their larger counterparts. These insights offer valuable reference points for both policymakers and business leaders aiming to formulate targeted strategies. Governments are encouraged to accelerate digital infrastructure deployment and tailor policy measures to fit firms of different sizes. Enterprises, in turn, should integrate digitalization into their core strategic planning, enhance their innovation capacity, and advance technological capabilities to foster a leap in new quality productivity.

Keywords: Digital transformation, new quality productivity of enterprisesl, Level of digital technology innovation, Investment in technological innovation.

1. Introduction

The 2024 Government Work Report prioritizes the acceleration of new quality productive forces, emphasizing the need to bolster original innovation, strategize future industries, and advance high-end, intelligent, and sustainable development. This strategic focus stems from China’s transitional economic phase, where conventional growth models—reliant on resource-intensive inputs, capital expansion, and low-cost labor—face diminishing marginal returns and faltering momentum. Simultaneously, escalating global competition in technology and the imperative for green transitions necessitate cultivating novel growth engines and reshaping industrial competitiveness. New quality productivity derives its impetus from breakthroughs in foundational and disruptive technologies, demanding a departure from path-dependent practices. The paradigm elevates the fusion of scientific innovation and industrial systems, with digital technologies (e.g., big data, AI, cloud computing) redefining production methodologies and organizational frameworks. As a pivotal enabler, digital transformation transcends mere operational adjustments; it reconfigures resource allocation, amplifies innovation capacity, and positions enterprises at the forefront of productivity leaps, thereby serving as a critical conduit for high-quality economic evolution.

As a key driver of new quality productive forces, enterprises are increasingly leveraging digital means to reshape production capacity and create value, making this a focal topic in both theoretical exploration and real-world application. From the standpoint of corporate governance, while digital transformation has generally reduced enterprise workforce sizes, it has also contributed to the rise of highly skilled labor and improvements in employment structures (Gao et al., 2025) [1]. Moreover, the digitalization of enterprises has been shown to notably improve supply chain operations, particularly in highly market-oriented and competitive sectors (Li et al., 2025) [2]. From an innovation perspective, digital transformation has significantly advanced firms' technological innovation processes. It supports core competitiveness, strengthens internal management and financing systems, and boosts R&D investment, ultimately enhancing innovation quality and collaborative capabilities (Fang and Liu, 2024) [3]. Digital transformation has also improved firms' innovation performance, with artificial intelligence playing a crucial mediating role. This influence appears even more pronounced in state-owned enterprises (Ma et al., 2025) [4]. Some studies further argue that digital transformation positively influences ESG performance by improving the efficiency and effectiveness of green technology initiatives (Chu et al., 2025) [5]. Additionally, AI greatly facilitates the advancement of new quality productivity through various pathways such as strategic planning, technological application, and innovation. Its impact is especially evident in private firms led by digitally proficient managers operating in intensely competitive markets (Li et al., 2025) [2]. Recent empirical research confirms that AI plays a substantial role in driving new quality productivity. As a crucial component of digital transformation, AI not only enhances innovation outcomes but also significantly contributes to labor structure optimization and enterprise resilience amid digital transition (Zhou et al., 2025) [6].

Despite growing attention, research on new quality productivity at the firm level remains at an early stage, with much of the existing literature focused on theoretical exploration and macro-level policy discussions. Empirical investigations into how businesses can effectively achieve improvements in this new form of productivity through digital transformation are still relatively limited. To bridge this research gap, the present study utilizes panel data from Chinese A-share listed firms spanning 2015 to 2022 to systematically assess the mechanisms through which digital transformation influences new quality productivity at the enterprise level. The core contributions of this paper are threefold: First, it addresses the shortage of firm-level empirical evidence linking digital transformation with advancements in new quality productivity. Unlike prior studies concentrated on broader economic or industry-wide perspectives, this research takes a micro-level approach using quantitative methods. Second, it introduces a novel methodological design, combining multiple regression analysis with mediation effect modeling. It identifies two intermediary channels—digital technological innovation and investment in innovation—and further explores the moderating impact of firm size via heterogeneity analysis. Third, the study emphasizes practical policy implications. Based on empirical findings, it offers differentiated recommendations aimed at enabling governments to tailor supportive measures and helping enterprises to implement targeted transformation strategies, thus enhancing the study's real-world relevance and application.

2. Theoretical models and research hypotheses

2.1. Digital Transformation and New Quality Productivity of Enterprises

Existing literature predominantly explores new quality productivity through qualitative frameworks, whereas empirical investigations into its relationship with digital transformation remain limited. Current studies suggest two key pathways through which digitalization influences enterprise productivity. First, digital transformation redefines production paradigms by integrating novel technologies, models, and elements. By harnessing capabilities in data aggregation, analysis, and application (Wang et al., 2024) [6], enterprises gain precision in identifying consumer demands and optimizing resource allocation. The adoption of artificial intelligence further substitutes repetitive tasks, fostering human-machine synergy and elevating labor efficiency. Such technology-driven

innovation establishes a productivity framework characterized by digital integration, thereby accelerating enterprise development. Second, digital transformation catalyzes organizational restructuring. Traditional hierarchical systems struggle to adapt to rapid technological shifts and global dynamics, necessitating agile management principles (Mihu et al., 2023) [7]. The dissolution of departmental silos and implementation of digital platforms enable flatter organizational architectures, facilitating real-time information flow and cross-functional collaboration. This structural agility enhances responsiveness to market fluctuations and strengthens supply chain coordination. Concurrently, digital ecosystems allow enterprises to unify internal and external resources, optimizing collaborative efficiency. Collectively, these institutional adaptations provide a foundation for advancing new quality productivity. Based on the above analysis, digital transformation can further promote the improvement of new productivity in enterprises by enhancing their production efficiency and promoting internal organizational changes. Based on this, this paper proposes Hypothesis 1.

In summary, digital transformation elevates enterprise productivity through dual mechanisms, technological empowerment and organizational modernization. Consequently, this study posits the following hypothesis:

Hypothesis 1: Digital transformation helps enhance the new quality productivity level of enterprises.

2.2. The mediating role of digital technology innovation level

Digital transformation is not only the inevitable path for enterprises to adapt to the external environment, but also the fundamental driving force for promoting technological progress and capability improvement within enterprises. Firstly, during the process of digital transformation, enterprises have significantly enhanced their digital technology innovation capabilities by introducing digital infrastructure, promoting data governance systems, and optimizing information systems. These technological innovations are not only reflected in the adoption of technologies, but also in the enterprises' independent research and development capabilities, the expansion of digital application scenarios, and the application of cutting-edge technologies. To achieve this goal, digital transformation enhances innovation efficiency by accelerating the conversion of R&D activities into patents and shortening the time between patent applications and approvals (Qiao et al., 2025) [8].

Secondly, the level of digital technology innovation converts the technological foundation provided by digital transformation for enterprises into productivity. From the perspective of the dynamic capability theory, for an enterprise to continuously gain a competitive advantage in a rapidly changing environment, it must possess the ability to perceive opportunities, capture resources and restructure. In the process of promoting digital transformation, enterprises do not passively adopt technologies but actively explore how to integrate technologies with themselves. Only through internal technological innovation can enterprises build digital solutions that match their strategies and achieve resource reconfiguration and capability upgrading. In other words, only when the level of digital technology innovation is high enough can enterprises grasp the potential value brought by digitalization, thereby promoting the formation of new quality productivity characterized by knowledge, data and technology-driven (Fang and Liu, 2024) [3].

Based on the above analysis, this paper proposes Hypothesis 2.

Hypothesis 2: Digital transformation can enhance the new quality productivity level of enterprises through the level of digital technology innovation.

2.3. The mediating role of technological innovation investment

Digital transformation fundamentally reshapes enterprise operations and resource allocation while necessitating strategic adaptations in innovation approaches. To sustain digital infrastructure and data capabilities, firms must prioritize financial commitments to technological advancements. Such investments serve as the cornerstone for cultivating new quality productivity, which hinges on the synergistic integration of technological, intellectual, and human capital elements. By enhancing

innovation performance and incentivizing R&D engagement (Yu et al., 2024) [9], digital transformation creates a self-reinforcing cycle: enterprises leverage their digital competencies to secure funding, which in turn accelerates the adoption of emerging technologies and perpetuates iterative innovation.

Consequently, this study advances the following hypothesis:

Hypothesis 3: Digital transformation can enhance the new quality productivity level of enterprises through technological innovation investment.

3. Research design and variable description

3.1. Data source

This study utilizes panel data from A-share listed companies in China (2015–2022), sourced from the CSMAR database. To ensure data integrity, the sample was refined through two criteria: (1) exclusion of financially distressed ST/*ST firms and (2) removal of entities with incomplete key variables.

3.2. Variable Selection and Explanation

3.2.1. Explained variable

New Quality Productivity (Npro): Drawing on the conceptual framework of Song et al. (2024) [10], this metric evaluates productivity advancements across three dimensions: labor capacity, labor objects, and production tools. An entropy weighting method was applied to compute indicator weights, generating annual enterprise-level indices for 2015–2022.

3.2.2. Explanatory variables

Digital Transformation (DCG): Adopting the keyword frequency approach by Wu et al. (2021) [11], this variable quantifies enterprise-level digital adoption by tallying mentions of artificial intelligence, big data, cloud computing, and blockchain in annual reports.

3.2.3. Mediation variable

This study incorporates the degree of digital technological innovation (Dig) and technological innovation investment (RD) as intermediary variables. It examines the influence of digital transformation on new quality productivity from the dual perspectives of financial input and technological contribution. The extent of digital innovation is assessed by taking the natural logarithm of one plus the number of digital patent applications filed by a firm, drawing on the statistical framework (Huang et al., 2023) [12]. Meanwhile, investment in technological innovation is quantified by calculating the ratio of a company's annual R&D expenditure to its total assets.

3.2.4. Control variables

To control other enterprise characteristic factors that may affect the productivity of new quality and ensure the accuracy of the research. Select the following variables as control terms: (1) Asset-liability ratio (Lev); (2) Enterprise size; (3) Cashflow (4) Enterprise age (Age) (5) Audit opinion type (Opinion) (6) Proportion of independent directors (Bi) (7) Board size. The specific definitions of the variables in this article are shown in Table 1.

Table 1. Variable definitions and explanations

Type	Name	Symbol	Definition and Explanation	References
Dependent Variable	Enterprise new quality productivity	Npro	Entropy method	(Song et al., 2024) [10]
Independent Variable	Digital transformation	Dcg	Logarithm of the total frequency of digitalization-related terms in annual reports plus one	(Wu et al., 2024) [11]
Mediator Variable	The level of digital technological innovation	Dig	Natural logarithm of number of digital patent applications plus one	(Huang et al., 2023) [12]
	Technological innovation investment	Rd	Firm's annual R&D expenditure as a proportion of total assets	(Wang et al., 2025) [13]
Control Variable	Asset-liability ratio	Lev	Debt to asset ratio	(Yang and Deng, 2023) [14]
	Enterprise size	Size	Logarithm of operating revenue	(Chu et al., 2025) [5]
	Cash flow	Cf	Net cash flow from operating activities as proportion of total assets	(Xu et al., 2024) [15]
	Enterprise age	Age	Difference between current year and IPO year	(Chen et al., 2023) [16]
	Board size	Board	Proportion of independent directors on the board	(Huo and Cheng, 2023) [17]
	Proportion of independent directors	Bi	Natural logarithm of number of board members	(Chu et al., 2025) [5]
	Audit opinion type	Opinion	Audit opinion dummy equals one if unqualified opinion, zero otherwise	(Song et al., 2024) [10]

3.3. Model Design

To verify H1, this paper establishes the following regression model to test the direct impact of digital transformation on the new quality productivity of enterprises.

$$Npro_{i,t} = \alpha_0 + \alpha_1 Dcg_{i,t} + \alpha_2 Controls_{i,t} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

Npro is the explained variable, representing the new quality productivity of the enterprise. Dcg is an explanatory variable, representing the situation of an enterprise's digital transformation; Controls represents the set of control variables; ε is the random disturbance term; The subscripts i and t represent individual enterprises and time respectively. If α1 is significantly positive, it indicates that digital transformation can enhance the development level of new quality productivity in enterprises.

To verify H2, this paper establishes the following multiple regression model:

$$Dig_{i,t} = \alpha_0 + \alpha_1 Dcg_{i,t} + \alpha_2 Controls_{i,t} + +\mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

Model (2) examines the impact of digital transformation on the level of digital technology innovation of enterprises. Among them, Dig is the mediating variable, and the other variables remain consistent with Model (1).

$$Rd_{i,t} = \alpha_0 + \alpha_1 Dcg_{i,t} + \alpha_2 Controls_{i,t} + +\mu_i + \lambda_t + \varepsilon_{it} \quad (3)$$

Model (3) examines whether digital transformation affects the investment in technological innovation, where Rd is the mediating variable, and the other variables remain consistent with Model (1).

To further examine whether investment in technological innovation and the level of digital technological innovation play a mediating role between digital transformation and the new quality productivity of enterprises, this paper constructs Model (4) and Model (5):

$$Npro_{i,t} = \alpha_0 + \alpha_1 Dcg_{i,t} + \alpha_2 Dig_{i,t} + \alpha_3 Controls_{i,t} + +\mu_i + \lambda_t + \varepsilon_{it} \quad (4)$$

$$Npro_{i,t} = \alpha_0 + \alpha_1 Dcg_{i,t} + \alpha_2 Rd_{i,t} + \alpha_3 Controls_{i,t} + +\mu_i + \lambda_t + \varepsilon_{it} \quad (5)$$

In Model (4), α_2 captures the effect of digital transformation on enterprise new quality productivity after accounting for digital innovation levels, while α_1 denotes the combined influence of digital transformation and its mediating variable (digital innovation) on productivity when controlling for baseline digital transformation effects. A statistically significant α_2 confirms the mediating role of digital innovation. All other variables in Model (5) mirror those in Model (1).

For Model (5), α_2 reflects the impact of digital transformation on productivity after adjusting for R&D investment intensity, with α_1 representing the joint effect of digital transformation and its mediator (R&D investment). Significant α_2 values validate R&D investment's mediating function. Variables in Model (4) remain identical to those in Model (1).

4. Empirical Analysis

4.1. Descriptive statistics and correlation analysis

Table.2. displays the descriptive statistics for all variables. A notably high standard deviation in technological innovation investment suggests considerable variability in how firms allocate resources toward green innovation. Likewise, both the mean and dispersion of digital technological innovation highlight pronounced differences in digital innovation capabilities across enterprises. The substantial fluctuation in cash flow, evidenced by its large standard deviation, indicates diverse liquidity conditions among the sampled firms. These findings offer a strong empirical basis for exploring corporate behavior and the factors that shape it.

Table 2. Descriptive statistics of variable

Variable	Obs	Mean	Std. Dev.	Min	Max
id	12800	247356.41	251055.34	8	603997
year	12800	2018.5	2.291	2015	2022
Npro	12800	2.794	0.422	1.191	6.617
Dcg	12800	18.666	42.482	0.001	547
Dig	12800	2.039	1.728	0.001	8.867
Rd	12800	0.023	0.022	0.001	0.582
Lev	12800	0.409	0.186	0.014	0.981
Size	12800	21.625	1.541	11.667	28.351
Cf	12800	0.12	1.2	-15.451	76.137
Age	12800	9.402	6.354	0.001	32
Board	12800	8.445	1.606	3	17
Bi	12800	37.749	5.734	16.67	80
Opinion	12800	0.982	0.133	0.001	1

It can be seen from the correlation analysis results in Table.3. that most of the core variables show significant but weak positive correlations, and no serious multicollinearity problem is indicated. Specifically, there is a significant positive correlation between the level of new quality productivity of enterprises and the levels of digital transformation and digital technology innovation, indicating that while enterprises enhance their digital capabilities and promote technological innovation, they can effectively strengthen their ability for high-quality development. In terms of control variables, there is a significant positive correlation between enterprise size and the asset-liability ratio, reflecting that large enterprises usually have stronger financing capabilities and more diverse capital structures. The proportion of independent directors is significantly negatively correlated with the number of board members, which may imply that when the size of the board expands, the proportion of independent directors tends to dilute, and also reflects the structural differences in the governance mechanism. The correlation between the audit opinion and most variables is not significant. It only

has a slight relationship with the enterprise size and the asset-liability ratio, indicating that it is more likely to be influenced by the external audit system or industry norms rather than the internal characteristics of the enterprise.

Table 3. Pairwise correlations

Variables	Npro	Dcg	Dig	Rd	Lev	Size	Cf	Age	Board	Bi	Opinion
Npro	1.000										
Dcg	0.158*	1.000									
Dig	0.173*	0.229*	1.000								
Rd	-0.003	0.045*	-0.035*	1.000							
Lev	-0.020*	-0.062*	0.228*	-0.079*	1.000						
Size	-0.033*	-0.028*	0.253*	-0.099*	0.381*	1.000					
Cf	-0.007	-0.012	-0.011	0.006	-0.035*	-0.007	1.000				
Age	0.000	-0.046*	0.073*	-0.116*	0.157*	0.134*	-0.002	1.000			
Board	-0.006	-0.039*	0.056*	-0.052*	0.146*	0.199*	-0.002	0.079*	1.000		
Bi	0.035*	0.035*	0.034*	0.041*	-0.006	-0.014	-0.008	-0.025*	-0.530*	1.000	
Opinion	-0.003	-0.023*	0.021*	-0.022*	-0.061*	0.056*	0.004	-0.012	0.011	0.017*	1.000

**** p<0.01, ** p<0.05, * p<0.1*

Notes:

This table reports the Pearson correlation coefficients among the main variables.

*P-values are reported in parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.*

4.2. Baseline Regression

A regression analysis was performed using Model (1), with results detailing the relationship between digital transformation and enterprise new quality productivity summarized in Table.4. Column (1) displays outcomes excluding control variables, while Column (2) incorporates these adjustments. The analysis reveals a consistent regression coefficient of 0.002 for digital transformation across both specifications, statistically significant at the 1% level ($p < 0.01$). This indicates a robust positive association: enterprises with higher degrees of digital transformation exhibit elevated levels of new quality productivity. These findings empirically validate the hypothesis that digital transformation actively stimulates the advancement of new quality productivity in enterprises, thereby confirming Hypothesis 1.

Table 4. Baseline Regression

	(1)	(2)
	Npro	Npro
Dcg	0.002***	0.002***
	(0.000)	(0.000)
Lev		-0.008
		(0.022)
Size		-0.009***
		(0.003)
Cf		-0.002
		(0.003)
Age		0.001
		(0.001)
Board		0.008***
		(0.003)
Bi		0.003***
		(0.001)
Opinion		0.005
		(0.028)
_cons	2.765***	2.764***
	(0.004)	(0.069)
N	12800	12800
r2	0.025	0.027

Standard errors in parentheses
** p < 0.1, ** p < 0.05, *** p < 0.01*

4.3. Analysis of mediating effect

4.3.1. Digital transformation, digital technology innovation and new quality productivity of enterprises

Table.5. explores the interplay among digital transformation, digital technology innovation, and firms' new quality productivity. In Column (1), the regression analysis reveals a coefficient of 0.010 for digital transformation's impact on digital innovation, signifying that digital transformation notably fosters advancements in digital technologies. Column (2) reports that the coefficient of digital technological innovation on new quality productivity is 0.041, which is significantly positive, demonstrating that improvements in digital technology contribute meaningfully to productivity gains. Additionally, the coefficient for digital transformation in Column (2) stands at 0.001 and remains statistically significant, confirming that digital transformation not only has a direct effect on new quality productivity but also exerts an indirect influence via digital innovation. These findings suggest that digital technology innovation serves as a partial mediator in the relationship between digital transformation and new quality productivity, thereby affirming Hypothesis Two. While the mediating role of digital innovation is evident, the primary influence still stems from the direct pathway, underscoring the need for integrated efforts in both R&D and the effective application of digital technologies to fully realize their potential.

Table 5. Digital Transformation, Digital Technology Innovation and New Quality Productivity of Enterprises

	(1)	(2)
	Dig	Npro
Dcg	0.010***	0.001***
Dig		0.041***
		(0.002)
_cons	-4.429***	2.944***
	(0.264)	(0.069)
N	12800	12800
r2	0.147	0.051

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.3.2. Digital transformation, technological innovation investment and new quality productivity of enterprises

Table.6. investigates the interrelationship among digital transformation, investment in technological innovation, and new quality productivity in the context of Hypothesis 2. Column (1) reveals that digital transformation influences new quality productivity through the channel of innovation investment. However, Column (2) shows that such investment exerts a suppressive effect on new quality productivity. Despite this, the coefficient for digital transformation remains significantly positive in Column (2), implying that digital transformation continues to directly enhance productivity outcomes. These results suggest that technological innovation investment serves as a weak negative mediator in the link between digital transformation and productivity improvement, likely due to inefficiencies or misaligned innovation strategies within firms. Thus, it becomes necessary to improve the effectiveness and direction of such investments. Consequently, Hypothesis 2 is not supported.

Table 6. Digital transformation, technological innovation investment and new quality productivity of enterprises

	(1)	(2)
	Rd	Npro
Dcg	0.001***	0.002***
Rd		-0.246
		(0.169)
_cons	0.048***	2.776***
	(0.004)	(0.069)
N	12800	12800
r2	0.025	0.028

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.4. Robustness test and endogeneity test

4.4.1. Replace the explanatory variable

This paper verifies the robustness of the results by adjusting the measurement method of the core variables. Therefore, in this paper, the measurement method for the explanatory variable digital transformation was changed from referring to the measurement method of Wu Fei et al. in 2021 [11] to referring to the measurement method of Zhen Hongxian et al. in 2023[18], denoted as Dcg1. Regression was re-conducted based on the new sample, as shown in columns (1) and (2) of Table.7. The coefficient of Dcg1 is 0.001, and the results are still significant, passing the robustness test.

4.4.2. Lagging explanatory variable

To address potential endogeneity in the variable test results, this study applies a one-period lag to the explanatory variable. The regression findings indicate that digital transformation plays a positive role in advancing new quality productivity within firms. Nevertheless, a potential bidirectional causality may exist, as higher levels of new quality productivity could enable enterprises to accumulate more financial and technological resources, thereby facilitating greater investment in digital transformation. To mitigate this issue, the analysis incorporates a one-period lagged version of the digital transformation variable, referred to as Ldcg. The results, presented in Column (3), report a digital transformation coefficient of 0.002, which remains significantly positive. This outcome implies that endogeneity has not meaningfully distorted the study's conclusions.

Table 7. Robustness test and endogeneity test

Robustness test			Endogeneity test	
	(1)	(2)		(3)
	Npro	Npro		Npro
Dcg1	0.001***	0.001***	Ldcg	0.002***
	(0.000)	(0.000)		(0.000)
Lev		0.014	Lev	-0.017
		(0.024)		(0.023)
Size		-0.008***	Size	-0.008***
		(0.003)		(0.003)
Cf		-0.002	Cf	-0.003
		(0.003)		(0.003)
Age		0.001	Age	0.001
		(0.001)		(0.001)
Board		0.009***	Board	0.009***
		(0.003)		(0.003)
Bi		0.003***	Bi	0.004***
		(0.001)		(0.001)
Opinion		0.022	Opinion	-0.002
		(0.032)		(0.029)
_cons	2.768***	2.702***	_cons	2.728***
	(0.004)	(0.074)		(0.073)
N	10752	10752	N	11200
r2	0.027	0.029	r2	0.032

4.5. Heterogeneity Analysis

The digital transformation capabilities of enterprises of different scales vary. To explore the differences in the impact of digital transformation on new quality productivity among enterprises of different scales, this study divided the sample into large enterprises and small enterprises based on the median operating income of enterprises (Wu, 2024) [19]. The results are shown in Table.8. The coefficient of new quality productivity of digital transformation for large enterprises is 0.001, and for small enterprises, it is 0.002. Both are significant. However, the promoting effect of digital transformation on the new quality productivity of small enterprises is significantly higher than that of large enterprises. This might stem from the fact that small businesses have flexible organizational structures and less resistance to transformation [20], enabling them to integrate digital technologies into their core businesses more efficiently. From the above results, it can be seen that in the process of supporting the digital transformation of enterprises, it is necessary to treat large and small enterprises differently. Meanwhile, large enterprises need to balance economies of scale and innovation investment, and enhance new quality productivity by maximizing digital technologies.

Table 8. Heterogeneity Analysis

	(1) Large enterprises	(2) small enterprises
	Npro	Npro
Dcg	0.001***	0.002***
	(0.000)	(0.000)
Lev	-0.093***	0.039
	(0.034)	(0.030)
Size	0.019***	-0.041***
	(0.006)	(0.007)
Cf	-0.006***	0.005
	(0.002)	(0.005)
Age	0.001	-0.001
	(0.001)	(0.001)
Board	0.014***	-0.004
	(0.003)	(0.004)
Bi	0.002**	0.002*
	(0.001)	(0.001)
Opinion	0.041	-0.017
	(0.038)	(0.037)
_cons	2.105***	3.575***
	(0.124)	(0.172)
N	6352	6448.000
r2	0.030	0.034

Standard errors in parentheses
** p < 0.1, ** p < 0.05, *** p < 0.01*

5. Conclusions and Implications

5.1. Research conclusion

As a pivotal driver of high-quality enterprise development, digital transformation (DT) elevates new quality productivity and serves as a cornerstone for national economic advancement. Leveraging panel data from Chinese listed firms (2015–2022), this study investigates DT's impact on enterprise productivity and its underlying mechanisms. Empirical results demonstrate that DT significantly boosts new quality productivity, with further analysis revealing dual mediation pathways: (1) strengthening digital innovation capabilities and (2) amplifying R&D investment intensity. Notably, digital innovation exhibits a robust mediating effect, whereas R&D investment shows limited efficacy, highlighting persistent challenges in translating financial commitments into tangible innovation outputs. Heterogeneity analysis further underscores that DT's productivity-enhancing effects are particularly pronounced in small-scale enterprises, suggesting scalability advantages in resource-constrained contexts.

5.2. Countermeasures and Suggestions

For the government, the first step is to accelerate the construction of digital infrastructure to provide solid support for the digital transformation of enterprises. Secondly, different support policies should be formulated based on the specific circumstances of the enterprise. Empirical results show that small enterprises are more sensitive to the improvement of new quality productivity in digital transformation. By enhancing the matching of subsidies and the level of service support, the government can fully unleash the flexible advantages of small enterprises in digital transformation. Therefore, the government can establish a list of limited digital fields, clearly encouraging specific directions such as big data modeling, AI, and remote collaboration, to help enterprises reduce inefficient investment caused by wrong directions. Secondly, the government can enhance the expert review mechanism, provide professional technical guidance and assessment mechanisms for small

and medium-sized enterprises, and score them from two dimensions: implement ability and implementation value. On this basis, subsidies will be given to enterprises. For large enterprises, it is necessary to encourage them to play a role of technology-driven and collaborative innovation in the industrial chain.

For enterprises, digital transformation should be regarded as the core development strategy. For small and medium-sized enterprises, it is necessary to give full play to the characteristics of flexible organization and rapid response, proactively transform in line with policy guidance, and focus on developing digital technology scenarios that are deeply integrated with their main business. For large and medium-sized enterprises, efforts should be made to build a complete digital governance system and balance the relationship between scale expansion and technological innovation.

5.3. Insufficient research

There are still some deficiencies in this paper in terms of sample selection, research methods and heterogeneity analysis. Firstly, the data used in this article covers the period from 2015 to 2022. Although it has a certain degree of timeliness, it cannot capture the long-term trend of digital transformation over a longer period. Secondly, in this paper, the level of digital technological innovation and technological innovation investment are selected as mediating variables, which fail to fully cover other possible transmission mechanisms. Furthermore, although this paper conducts a partial heterogeneity analysis of the road, the internal differences within specific industries have not been deeply explored yet. In the future, more targeted studies can be carried out for different industries.

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