International Journal of Economics and Finance; Vol. 17, No. 2; 2025
ISSN 1916-971X E-ISSN 1916-9728
Published by Canadian Center of Science and Education

Analysis of the Influence Mechanism of Digital Transformation on the New Quality Productivity of Enterprises --The Mediating Role of Financing Constraints and ESG Ratings

Yichun Zhang[1] & Xinyi Zhang[2]

[1] School of Economics, Northwest University for Nationalities, Lanzhou, China

[2] School of Financial Management, University of International Business and Economics, Shanghai, China

Correspondence : Yichun Zhang, School of Economics, Northwest University for Nationalities, Lanzhou, China. Tel: 183-3489-8992. E-mail: 2393430298@qq.com

Received: November 6, 2024 Accepted: December 6, 2024 Online Published: December 20, 2024

doi:10.5539/ijef.v17n2p15 URL: https://doi.org/10.5539/ijef.v17n2p15

Abstract

Based on the panel data of A-share listed companies from 2011 to 2022, this paper empirically tests the impact and transmission mechanism between enterprise digital transformation and enterprise new quality productivity. The results show that enterprise digital transformation has a significant driving effect on enterprise new quality productivity, and the conclusion still holds after a series of robustness tests. In terms of the impact mechanism, firms drive the level of firms' new quality productivity by alleviating financing constraints and improving firms' ESG performance, and digital transformation significantly enhances new quality productivity in SOEs, large firms, and technology-intensive industries.

Keywords: digital transformation, ESG performance, financing constraints, new quality productivity

1. Introduction

In September 2023, General Secretary Xi Jinping first put forward the concept of "new quality productivity" when he hosted a symposium on promoting the comprehensive revitalization of the Northeast in the new era. According to General Secretary Xi Jinping's discussion on new productivity qualities when he presided over the 11th Collective Learning Session of the Political Bureau of the Central Committee, new quality productivity is an advanced productivity model that is led by innovation, free from the constraints of the traditional economic growth mode and the development path of productivity, and characterized by high technology, high efficiency, and high quality, and is in line with the new development concept. The concept of new quality productivity not only further enriches the definition of productivity, but also provides a clear direction and impetus for China's future economic growth. Since the reform and opening up, China's economy has experienced a period of rapid growth for more than 40 years, and has made a series of great achievements, creating a miracle of economic development that is rare in the world. Digital transformation is changing the structure of production and operation, giving rise to new production concepts and management paradigms, continuously optimizing resource allocation, promoting industrial integration and interconnection, and is a key force and strategic goal for driving economic development. The competitiveness of national industries depends on the emergence of new quality productivity, which is based on digital transformation. Therefore, it is of practical significance to study the impact of digital transformation on new quality productivity.

2. Literature Review

The definitional framework and measurement methods of digital transformation have become mature. The process aims to enhance the market competitiveness of enterprises by integrating digital technologies into traditional production management, sales and other activities, and then revolutionizing business models and operation strategies. For the measurement of digital transformation, academics generally adopt both quantitative analysis and textual analysis. The former quantifies the extent of digital transformation based on the proportion of digital transformation-related intangible assets in the overall intangible assets of an enterprise; the latter constructs a thesaurus containing keywords for digital transformation and assesses the depth of digital transformation by counting the frequency of these keywords in the annual reports of enterprises.

In contrast, the research on the conceptual definition and measurement of new quality productivity is still in the initial exploration stage. According to the important exposition of General Secretary Xi Jinping, the new quality productivity is defined as an advanced productivity form with high-tech content, high-efficiency output, and high-quality features, which is innovation-led and able to break away from the traditional economic growth model and productivity development path, and its core concept is in line with the new development concept. On this basis, the academic community has launched a multi-dimensional research around the new quality productivity. At the macro level, Fuxian et al. (2024) quantitatively compared the level of new quality productivity of cities in the four major economic regions of China based on the three major elements of new quality laborers, labor objects, and labor materials using a projection clustering model; while Ling et al. (2024) interpreted the new quality productivity as “talent leadership” as the cornerstone, “technological innovation” as the foundation, and “technological innovation” as the core of new quality productivity. Ling et al. (2024) interpreted NQP as a new productivity model with “talent leadership” as the cornerstone, “scientific and technological innovation” as the primary driving force, “industrial empowerment” as the external manifestation, and “high-quality development” as the ultimate goal. At the micro level, Donglin and Meixuan (2024) point out that SOEs should focus on the three elements of the new quality productivity - high-quality labor, high-technology labor materials and high-efficiency labor objects, and comprehensively promote the transformation and upgrading of enterprises in order to enhance the level of new quality productivity. Song Jia et al. (2024), on the other hand, from the theory of two factors of productivity, decomposed the new quality productivity of enterprises into four dimensions: live labor, materialized labor, hard technology and soft technology, and measured them by using the entropy value method. In this paper, the new quality productivity is defined as the contemporary advanced productive forces that have been spawned by revolutionary technological breakthroughs, innovative allocation of factors of production, and in-depth transformation and upgrading of industries. It takes the qualitative change of workers, labor materials, labor objects and their optimal combination as the basic connotation, which is mainly manifested in the significant increase of total factor productivity.

Research on digital transformation and new quality productivity is still somewhat problematic, with only a few literatures exploring the impact of digital transformation on firms’ new quality productivity. For example, Karacuka (2024) focuses on exploring how digital transformation affects new dimensions of firm productivity. Focusing on the innovation of labor tools, some scholars have analyzed the direct impact of digital transformation on firms’ innovation efficiency as well as the possible threshold effect (Aaronson, 2024). At the same time, some researchers have explored issues such as the value-added labor skills and changes in labor income brought about by digital transformation from the perspective of labor quality improvement.

In view of this, based on the internal and external perspectives of enterprises, this paper not only discusses in depth the influence mechanism of enterprise digital transformation on the new quality productivity, but also analyzes the intermediary role of financing constraints and ESG performance, aiming to provide theoretical support and practical guidance for the enhancement of the new quality productivity of enterprises. The innovative contributions of this paper are mainly reflected in the following three aspects: first, this paper combines enterprise digital transformation with new quality productivity, which broadens the horizons of existing research; second, from the new perspective of financing constraints and ESG ratings, it reveals their mediating effects in the process of digital transformation affecting the new quality productivity of enterprises, which further improves the theoretical framework of the impact of digital transformation on the new quality productivity; and finally. This paper also explores the heterogeneous characteristics of the impact of digital transformation on the new quality productivity of enterprises from the dimensions of the nature of enterprise property rights, enterprise size and labor intensity, which provides rich empirical evidence and practical insights for related research.

3. Theoretical Analysis and Research Hypotheses

3.1 The Direct Impact of Digital Transformation on the New Productivity of Enterprises

The new productivity is mainly focused on the rise of strategic emerging industries and future industries, and its core driving force covers the three dimensions of technological innovation, management innovation and model innovation. Digital transformation plays a crucial role in this process, facilitating the realization of technological innovation by improving production efficiency and refining production processes. By introducing cutting-edge production strategies and building standardized management paradigms, it promotes the deepening of management innovation; and by exploring innovative development models and building innovation ecosystems, it accelerates the pace of model innovation. Specifically, the synergistic effect of technological innovation, management innovation and model innovation has provided a strong impetus for the development of strategic emerging industries typified by new materials, new energy, biotechnology and advanced manufacturing, as well as future industries represented by robotics, quantum information science, artificial intelligence, industrial Internet, satellite Internet and so on. This comprehensive innovation system not only promotes the vigorous development of these industries, but also gives rise to the remarkable emergence of new-quality productive forces, marking a profound change in the form and structure of productive forces.

Based on this, this paper proposes hypothesis H1: digital transformation can improve the level of new quality productivity.

3.2 The Indirect Impact of Digital Transformation on the New Quality Productivity of Enterprises

3.2.1 Digital Transformation, Financing Constraints, New Quality Productivity

Digital transformation has demonstrated remarkable effectiveness in alleviating enterprise capital constraints and reducing financing burdens. Given that R&D and innovation activities are inherently capital-intensive, characterized by high return uncertainty and long payback cycles, enterprises must rely on sufficient capital reserves to effectively protect against potential risks when promoting such activities. In this context, digital transformation becomes an effective strategy. Digital transformation optimizes the resource allocation structure by streamlining the investment of labor resources, enabling enterprises to shift more funds to the investment of other key and scarce resources, thus effectively reducing internal capital constraints. At the same time, digital transformation also greatly promotes the construction and interconnection of business platforms within the same industry and industry chain, which not only provides enterprises with a broader network of partners and investment institutions to contact, but also helps enterprises build a more robust cash flow system, thus effectively alleviating the external financial constraints. With the reduction of financial constraints on enterprises, the innovation level of their labor tools and productivity have been significantly improved. This change not only promotes the progress of enterprise productivity, but also positively promotes the formation and development of new quality productivity, further highlighting the important role of digital transformation in promoting the high-quality development of enterprises.

Based on this, this paper proposes hypothesis H2: digital transformation improves the level of new quality productivity of enterprises by alleviating financing constraints.

3.2.2 Digital Transformation, Corporate ESG Performance, and New Quality Productivity

Digital transformation contributes significantly to corporate environmental, social and governance (ESG) performance. First of all, at the level of environmental performance, digital transformation, through the technology spillover effect, accurately allocates enterprise resources, effectively reduces the consumption of non-essential resources, and then helps enterprises save energy and reduce emissions, striking a double balance between economic benefits and green benefits, and significantly optimizing the environmental performance of enterprises. In addition, digital transformation accelerates the information interaction between enterprises and the external environment, and its embedded openness, cooperation and sharing qualities promote cross-organizational collaboration and communication. Information sharing and knowledge integration among enterprises not only lowers the threshold of green technology application, but also promotes the widespread adoption and innovation of green technology, further enhancing the environmental performance of enterprises (Wang, 2024).

Second, in the dimension of resource integration, digital transformation realizes the deep integration of digital technology and traditional production mode, which provides rich knowledge and resource support for innovation activities, and strongly promotes the enhancement of green innovation capability. Enterprises are able to reorganize and optimize production resources, improve production efficiency, and achieve better output under the constraints of established innovation resources (Loebbecke & Picot, 2015). In this process, enterprises were equipped to efficiently integrate green technology resources and mastered stronger green innovation capabilities, which in turn helped them obtain more green patents. This undoubtedly provides strong support for enterprises to respond to environmental, social and governance challenges more efficiently, which in turn realizes the overall improvement of ESG performance.

By engaging in ESG practices, companies not only send positive signals to the outside world, but also help shape a greener and more responsible corporate image and enhance their social reputation. A good corporate image not only facilitates the acquisition of external resources, but also promotes the cultivation and introduction of talents. High-quality talents, as the core element of innovation and development, provide a solid talent base for enterprise R&D and innovation, and promote the continuous emergence of new productivity.

Based on this, this paper proposes hypothesis H3: digital transformation promotes new quality productivity of enterprises by improving ESG performance.

4. Research Design and Empirical Analysis

4.1 Variable Selection and Data Sources

4.1.1 Variable Selection

1) Explained variable: New quality productivity of enterprises (NPRO)

Drawing on the index system research of Song Jia et al. (2024) to establish the enterprise new quality productivity model, with the help of entropy weighting method for enterprise new quality productivity evaluation index assignment, to get the index of enterprise new quality productivity level of A-share listed companies in the period of 2010-2022, the specific index system is shown in Table 1.

Table 1. Indicators of new quality productivity of enterprises

Factor	Sub-factor	Indicator	Description	Weighting
Labor Force	Live Labor	R&D Staff Salary Percentage	R&D Expenses - Salary & Compensation / Operating Revenue	28
		Percentage of R&D	personnel Number of R&D personnel / Number of employees	4
		Percentage of highly educated personnel	Number of undergraduates or above / Number of employees	3
	Labor Objects	Fixed Assets Ratio	Fixed Assets/Total Assets	2
		Manufacturing expenses	(Subtotal of cash outflow from operating activities + depreciation of fixed assets + amortization of intangible assets + provision for impairment - Cash paid for purchases of goods and acceptance of services - Wages paid to and for employees) / (Subtotal of cash outflow from operating activities + depreciation of fixed assets + amortization of intangible assets + provision for impairment)	1
Production tools	Hard technology	R&D depreciation and amortization as a percentage	R&D expenses - depreciation and amortization / operating income	27
		R&D Lease Expense	R&D Expense - Lease Expense / Revenue	2
		R&D direct inputs	R&D expenses - direct inputs/revenue	28
		Intangible Assets	Intangible Assets/Total Assets	3
	Softtek	Total Asset Turnover Operating	Operating Income/Average Total Assets	1
		Inverse equity multiplier	Owners' equity/total assets	1
New Mass Productivity				100

2) Core explanatory variable: Enterprise digital transformation (DCG)

Drawing on the related study of Wu Fei et al. (2021), the enterprise digital transformation level variable was derived using text analysis.

3) Mediating variables

Corporate financing constraints are measured using the method of Kaplan et al. (1997), and the KZ index measuring financing constraints is constructed using regression coefficients, which is used as a mediating variable to measure the degree of corporate capital constraints; corporate ESG performance is measured using the CSI ESG ratings for the period of 2009-2023 to measure the ESG performance of corporations.

4) Control variables

Size, Lev, Roa, SOE, Age, TobinQ, Growth, Board and ATO are used as control variables. The data are obtained from the Cathay Pacific database.

4.1.2 Data Source

In view of the availability of data, the panel data of Chinese A-share listed companies during the period of 2011-2022 are selected as the sample. The data were screened as follows: 1) the samples of ST and *ST listed companies were excluded; 2) listed companies in the financial industry, real estate industry were excluded; (3) the samples of listed companies with significant omissions in financial data were deleted. The data information used is from the Cathay Pacific (CSMAR) database, Wind database and China Urban Statistical Yearbook, and finally 32,575 valid observations are obtained.

4.2 Model Construction

In order to study the specific impact of digital transformation on the new quality productivity of enterprises, this paper adopts a two-way fixed effects model, constructed as follows

$$Npro_{it} = \alpha_0 + \alpha_1 DCG_{it} + \alpha_2 Controls_{it} + \mu_i + \gamma_j + \varepsilon_{it} \quad (1)$$

Where, the explanatory variable in the econometric model is the new quality productivity of enterprises (NPRO), the digital transformation of enterprises (DCG) is the core explanatory variable, i denotes different enterprises, t denotes the year, $Controls_{it}$ is the control variable, μ_i denotes the fixed effect of the year, γ_j denotes the fixed effect of the industry, and the random error term is denoted by ε_{it}.

4.3 Analysis of Empirical Results

4.3.1 Descriptive Statistics

The descriptive statistics of variables are shown in Table 2. The minimum value of enterprise new quality productivity (NPRO) is 0.0396, and the maximum value is 804.4927, which is significantly different, and the mean value is much smaller than the maximum value, indicating that the level of new quality productivity of different enterprises varies greatly, and the overall level of new quality productivity of enterprises in China is relatively low, and there is still a great deal of room for the enhancement of the level of new quality productivity of enterprises. The mean value of digital transformation is 1.4337, the minimum value is 0.0000, and the maximum value is 6.3008, which means that some enterprises have not yet realized the importance of digitization, and there is a significant difference in the level of digitization among different enterprises.

Table 2. Descriptive statistics of the main variables

VarName	Obs	Min	Mean	Max	SD
Npro	32575	0.0396	5.1337	804.4927	5.1731
DCG	32575	0.0000	1.4337	6.3008	1.4095
Size	32575	15.5773	22.2412	28.6365	1.3135
Lev	32575	0.0071	0.4229	1.2379	0.2054
ROA	32575	-1.8591	0.0391	1.2848	0.0759
SOE	32575	0.0000	0.3282	1.0000	0.4696
Age	32575	2.0000	19.6367	65.0000	6.0029
TobinQ	32575	0.6245	2.0936	259.1459	2.5100
Growth	32575	-1.3092	4.9512	1.35e+05	750.4488
Board	32575	1.0986	2.1201	2.8904	0.1987
ATO	32575	-0.0479	0.6531	12.3729	0.5390

4.3.2 Baseline Regression Results

Table 3 Column (1) shows the direct regression results of the explanatory variables and the explained variables, column (2) shows the regression results with the addition of year and industry fixed effects, and column (3) shows the regression results with the addition of the control variables and the control of year and industry fixed effects, from the results, it can be seen that when the enterprise's digital transformation index rises by 1, the corresponding level of new-quality productivity increases by 0.1376 simultaneously, and the enterprise's The coefficients of digital transformation (DCG) are all significantly positive at the 1% level, indicating that enterprise digital transformation has a significant positive impact on new quality productivity, and hypothesis H1 holds.

Table 3. Baseline regression results

	(1)	(2)	(3)
	Npro	Npro	Npro
DCG	0.1376***	0.3247***	0.1379***
	(5.5278)	(16.0293)	(5.4826)
Size			0.1786***
			(6.2500)
Lev			-1.1192***
			(-6.1092)

ROA			-1.9799***
			(-4.7736)
SOE			0.6964***
			(10.0843)
age			-0.0423***
			(-7.7724)
TobinQ			0.0611***
			(5.1783)
Growth			0.0000
			(0.1425)
Board			0.4384***
			(2.9163)
ATO			-0.0317
			(-0.5485)
_cons	3.6123***	4.6681***	-0.5053
	(13.1272)	(114.6228)	(-0.7565)
Year	NO	YES	YES
Industry	NO	YES	YES
N	32575	32575	32575
Adj. R^2	0.052	0.008	0.059
F	56.4364	256.9394	50.7346

Note. * denotes p<0.1, ** denotes p<0.05, *** denotes p<0.01.

4.3.3 Robustness Test

To further ensure the robustness and credibility of the benchmark results, this paper also adopts the following methods for testing: (1) Replacement of explanatory variables. Drawing on the related study by Chenyu Zhao (2021), text analysis is used to measure the degree of enterprise digital transformation in order to improve the robustness of the regression results. The results in column (1) of Table 4 show that for every unit change in enterprise digital transformation (numA), the new quality productivity changes by 0.0085 units, and it positively affects the new quality productivity of enterprises at the 1% level, and the hypothesis H1 of this paper is verified. (2) Explanatory variables lagged one period. The robustness test is conducted by lagging one period of the explanatory variables, and the results in column (2) of Table 3 show that the coefficient of the explanatory variable lagged one period (L.DCG) is significantly positive at the 1% level, which indicates that the effect of the digital transformation on the promotion of new quality productivity of the enterprise can be maintained over a longer period of time, and the obtained conclusions are in line with the previous article, and the results are still robust. (3) Excluding the sample of abnormal years. During the sample period, the new crown epidemic after 2020 has a very significant impact on the development of enterprises, in order to reduce the uncertainty of the results of the study in abnormal years, the regression is conducted after excluding the three years of data from 2020-2022. The results in column (3) of Table 3 show that the coefficient of digital transformation of firms (DCG) is significantly positive, and the digital transformation of firms positively affects firms' new quality productivity at the 1% level, and hypothesis H1 is tested once again.

Table 4. Robustness test results

	(1) Replacement of explanatory variables	(2) Explanatory variables lagged one period	(3) Excluding outlier years
numA	0.0085***		
	(8.8954)		
DCG		0.1492***	0.1280***
		(8.2957)	(9.1643)
Size	0.1796***	0.1480***	0.0641***
	(6.3126)	(6.9409)	(4.0852)
Lev	-1.0942***	0.1660	-0.2008**
	(-5.9707)	(1.1686)	(-2.0350)
ROA	-1.8339***	-1.3003***	-1.0236***
	(-4.4159)	(-3.4266)	(-4.3509)

SOE	0.6973***	0.5908***	0.6537***
	(10.1228)	(13.3060)	(17.9128)
Age	-0.0423***	-0.0260***	-0.0179***
	(-7.7699)	(-6.1476)	(-5.8356)
TobinQ	0.0621***	0.1090***	0.0174***
	(5.2630)	(6.0726)	(3.1325)
Growth	0.0000	-0.0089	0.0000
	(0.1303)	(-0.4781)	(0.1519)
Board	0.4356***	0.5973***	0.3110***
	(2.8975)	(5.6971)	(3.8664)
ATO	-0.0585	-0.1178**	0.0832***
	(-1.0081)	(-2.5353)	(2.7312)
_cons	-0.4573	-0.2410	1.5740***
	(-0.6854)	(-0.4864)	(4.3714)
N	32536	11473	21290
Adj. R^2	0.060	0.265	0.216
F	51.9842	107.0133	155.3552

Note. * denotes p<0.1, ** denotes p<0.05, *** denotes p<0.01.

4.3.4 Endogeneity Test

Due to the possible reverse causality between digital transformation and firms' new quality productivity, i.e., firms with high quality of technological innovation, economic effectiveness and development will pay more attention to digital transformation, which will in turn increase the level of new quality productivity. To overcome this endogeneity, this paper chooses the 2SLS method for testing. In terms of selecting instrumental variables, referring to the idea of Mingyue (2022) and others, the mean value of the degree of digital transformation of other firms in the same industry in the same year is used as the instrumental variable of enterprise digital transformation IV. On the one hand, the digital transformation of enterprises is closely related to their industries, and they are facing similar market environments with other firms in the same industry, which satisfies the relevance of the instrumental variable; on the other hand, the mean value of the degree of digital transformation of other On the other hand, the degree of digital transformation of other enterprises in the same industry in the same year does not directly affect the new quality productivity of the enterprise, which satisfies the exogeneity of the instrumental variable.

Combined with the regression results in Table 5, it shows that the coefficient of the instrumental variable IV in the first stage is significantly positive under 1% confidence water, and the instrumental variable of digital transformation of the enterprise in the second stage and the new quality productivity of the enterprise are significantly positive at the 5% level. The weak instrumental variable test for the selected instrumental variables shows that the F-value is 327.56, which is greater than the critical value of 10, indicating that the selected instrumental variables are exogenous ruling out the weak instrumental variable problem. The values of Kleibergen-Paap rk LM and Kleibergen-Paap rk Wald F statistic were 655.55 and 392.19 respectively, which passed the instrumental variable validity test. As a result, under the scenario of considering endogeneity issues, enterprise digital transformation can still significantly and positively promote the new quality productivity of enterprises.

Table 5. Regression results of instrumental variables

	(1)	(2)
	Phase 1	Phase 2
	DCG	Npro
IV	0.540***	
	(-3.9558)	
DCG		0.9562**
		(2.0358)
_cons	1.580**	1.8998*
	(1.3421)	(1.92)
Controls	YES	YES
Year	YES	YES

Industry	YES		YES
Kleibergen-Paap rk		163.549	
LM statistic		655.55	
Wald F statistic		392.19	
N	32566		32566
Adj. R^2	0.954		0.925
F	327.5627		174.2037

Note. * denotes p<0.1, ** denotes p<0.05, *** denotes p<0.01.

4.3.5 Heterogeneity Analysis

Firms implementing digital transformation may have differentiated results on the improvement of new quality productivity level due to differences in individual characteristics. Therefore, this paper chooses to verify the impact of firms' heterogeneous characteristics on the improvement of new quality productivity level by digital transformation from three aspects: the nature of property rights, the intensity of factors and the level of regional digital infrastructure.

1) Nature of property rights

There are some differences between state-owned enterprises and non-state-owned enterprises in the ability to inject capital and the current return of attention, therefore, for enterprises with different property rights, there may be differences in the impact of digital transformation on the new quality of productivity, this paper will be divided into two parts of the sample of state-owned enterprises and non-state-owned enterprises for regression. According to columns (1) and (2) of Table 6, the regression coefficient of state-owned enterprises is 0.2484, which is higher than that of non-state-owned enterprises, suggesting that the implementation of digital transformation in state-owned enterprises can better improve the level of new quality productivity compared with non-state-owned enterprises. Exploring the root cause, perhaps it can be attributed to the fact that state-owned enterprises have more significant advantages of capital abundance, economies of scale and talent aggregation than other types of enterprises in the use of digital technology, the promotion of the digital transformation process, and the realization of key technological breakthroughs and innovations in key areas. These advantages provide solid support for state-owned enterprises, enabling them to make more outstanding progress in the above areas.

2) Enterprise size

Different enterprise sizes have different business capabilities. In order to test the differences in the impact of heterogeneity in enterprise size on the research findings, this paper divides large enterprises into a group and groups MSMEs into non-large enterprises. From the regression results in columns (3) and (4) of Table 6, the DCG coefficients of both large enterprises and non-large enterprises are significantly positive at the 1% level, indicating that digital transformation can promote the new quality productivity of enterprises of different sizes. However, the DCG coefficient of large enterprises is slightly higher than that of small and medium-sized enterprises, which may be due to the fact that large enterprises operate in a standardized manner and are well capitalized, while small and medium-sized enterprises operate in an unstandardized manner and the relevant information is not easily accessible.

Table 6. Heterogeneity regression results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	State-owned	Non-state-owned	Large	Small and medium-sized	Labor-intensive	Capital-intensive	Technology-intensive
DCG	0.2484***	0.1028***	0.1212***	0.1107***	0.2745***	0.3225***	0.3637***
	(10.7533)	(2.9629)	(6.8624)	(2.6098)	(5.6804)	(4.7520)	(3.1523)
Controls	YES	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES
Industry	YES	YES	YES	YES	YES	YES	YES
_cons	1.2263**	-0.9061	-2.9108***	-1.9368	-4.4376***	-3.0243***	1.4087***
	(2.3276)	(-0.8583)	(-5.2506)	(-1.0151)	(-3.2803)	(-5.9661)	(3.0879)
N	10691	21884	14246	18329	15249	5870	11143
Adj. R^2	0.256	0.040	0.268	0.030	0.038	0.143	0.257
F	93.0929	23.9615	131.2159	15.3172	24.9638	38.7393	108.2922

Note. * denotes p<0.1, ** denotes p<0.05, *** denotes p<0.01.

3) Factor intensity

Digital transformation requires a certain cost, which varies across industries with different factor intensities. Firms with a relative advantage in technology and capital factors can realize digital transformation at lower costs and higher efficiency, thus promoting the improvement of new quality productivity. Therefore, this paper refers to Shuguang and Jie (2018) and classifies the research sample into three categories of capital-intensive, technology-intensive, and labor-intensive firms according to the proportion of net fixed assets and the proportion of skilled personnel. According to columns (5) to (7) of Table 5, it can be seen that the effect of digital transformation on the new quality productivity level of enterprises is most obvious in technology-intensive enterprises, followed by capital-intensive enterprises, and the effect of labor-intensive enterprises is the worst. The reason for this may be that capital and technology-intensive enterprises themselves have the relative advantage of digital transformation, and their prior investment and technology accumulation are more sufficient in the process of building new quality productivity, so that they can make better use of the digital economy to improve the level of innovation and the efficiency of technological application, and realize faster progress in new quality productivity.

4.4 Mechanism Test

Combined with the characteristics of digital transformation and based on the theoretical analysis above, this paper will study the mechanism of digital transformation on the enhancement of the level of new quality productivity in 2 paths: financing constraints and enterprise ESG ratings.

4.4.1 Easing Financing Constraints

Enterprises implementing digital transformation will optimize the efficiency of internal capital allocation while optimizing the degree of digitization to ease the pressure of external financing, increase the possibility of obtaining policy subsidies and market investment, and provide financial security for innovative behavior and technological breakthroughs, which will ultimately be manifested in the increase in the level of new quality productivity of enterprises. Drawing on the methodology of Kaplan et al. (1997), this paper adopts sequential Logit regression method, selects cash flow ratio, enterprise debt ratio, cash stock ratio and other indicators for measurement, and constructs the KZ index measuring financing constraints with regression coefficients, which is used as a mediator variable measuring the degree of enterprises' financial constraints. According to columns (1) to (3) of Table 7, it can be seen that the coefficient of digital transformation is negative and significant at the 10% level, which indicates that the implementation of digital transformation has a significant reduction effect on the pressure of corporate financial constraints, while the rise in the pressure of financial constraints will be detrimental to the improvement of the level of new quality productivity of enterprises. Therefore, the hypothesis H2 of this paper is verified.

Table 7. Intermediary mechanism regression results

	(1) Npro	(2) Npro	(3) KZ Index	(4) Npro	(5) ESG
DCG	0.1311***	0.1318***	-0.0061*	0.1297***	0.0281***
	(20.6774)	(20.8288)	(-1.7031)	(20.4532)	(10.0144)
KZ		0.1124***			
		(21.1903)			
ESG				0.0496***	
				(7.2494)	
_cons	-1.0098***		5.1490***		-1.1727***
	(-6.1392)		(54.9822)		(-16.1307)
N	109208	109208	109208	109208	109208
Adj. R^2	0.208	0.211	0.633	0.208	0.145
F	736.5648	732.3238	4832.0845	719.8037	475.9498

Note. * denotes p<0.1, ** denotes p<0.05, *** denotes p<0.01.

4.4.2 Corporate ESG Ratings

In this paper, CSI ESG ratings are used to measure corporate ESG performance. In columns (4)-(5), the coefficient estimates between firms' digital transformation (DCG) and firms' ESG performance (ESG) are positive and significant at the 1% confidence interval, indicating that digital transformation contributes to firms'

ESG performance. The coefficient estimate of DCG in Column (5) has decreased and is significant at the 1% level, and the mediating effect holds. Based on the above analysis, digital transformation can promote new quality productivity by enhancing firms' ESG performance, therefore, hypothesis 3 is established.

5. Conclusion and Recommendation

This paper selects the heterogeneity factors of China's A-share listed companies in the years 2011-2022. It is empirically found that digital transformation can significantly increase the level of new quality productivity of enterprises, and this conclusion still holds after the robustness test. The mechanism test shows that digital transformation promotes the rise of firms' new quality productivity level by alleviating financial constraints and improving ESG performance. Heterogeneity analysis shows that state-owned enterprises, technology-intensive enterprises and enterprises with larger enterprise size have more obvious effects on the increase of new quality productivity level by implementing digital transformation. Based on the findings of the empirical analysis in this paper, the following policy insights can be obtained:

At the enterprise level, in the face of the global wave of digitization and informatization, enterprises should take the initiative to carry out digital trends, accelerate the pace of transformation, and absorb and cultivate professionals in the field of digitization. At the same time, enterprises should actively practice environmental, social and governance (ESG) principles, commit to reducing environmental pollution in production and operations, increase investment in green innovation, and demonstrate a responsible attitude toward the future. To this end, it is crucial to establish a sound information disclosure system to ensure the timeliness, accuracy and completeness of internal information, and to strengthen the technological capability of external information collection, so as to provide solid support for corporate decision-making and action with information superiority. Enterprises should actively explore diversified financing methods, such as obtaining low-interest loans through policy financial institutions or utilizing the capital market for equity financing, in order to alleviate the pressure on capital. At the same time, enterprises should also pay attention to optimizing internal capital management and improving the efficiency of capital use by reducing operating costs.

At the government level, one of the first steps is to continue to deepen the implementation of subsidy policies and continuously refine and optimize special support measures for enterprise digital transformation, with the aim of accelerating the cultivation and development of new productivity. On the other hand, given the significant differences in the role of digital transformation in promoting new productivity across different enterprise characteristics and industries, the government needs to play a leading role in adopting a "precise policy" strategy. Specifically, the government should customize support programs according to the specific industry segments, long-term development plans and current operating conditions of micro enterprises. Through precise digital intelligence empowerment, the government should promote the improvement of new productivity, ensure that enterprises can realize healthy growth in their respective fields, and contribute to the transformation and upgrading of the entire economic system.

References

Aaronson, S., Mann, C. L., & Syverson, C. (2024). Labor, investment, and technology: assessing the drivers of productivity growth. *Bus Econ.*, *59*, 154-165. https://doi.org/10.1057/s11369-024-00360-8

Achref, M., Jamel, C., & Tijani, A. (2024). Do business ethics moderate corporate corruption risk-ESG reporting relationship? Evidence from European ESG firms. *International Journal of Ethics and Systems*, *40*(4), 734-758. https://doi.org/10.1108/IJOES-07-2023-0166

Chenyu, Z., Wenchun, W., & Xuesong, L. (2021). How digital transformation affects corporate total factor productivity. *Finance and Trade Economics.* https://doi.org/10.19795/j.cnki.cn11-1166/f.20210705.001.

Donglin, S., & Meixuan, L. (2024). Dialectical Thinking on New Quality Productivity and High Quality Development of State-owned Enterprises. *Social Science Front. DataType.* Retrieved from https://kns.cnki.net/kcms2/article/abstract?

Fei, W., Huizhi, H., Huiyan, L. et al. (2021). Corporate digital transformation and capital market performance: Empirical evidence from stock liquidity. *Management World.* https://doi.org/10.19744/j.cnki.11-1235/f.2021.0097

Fuxian, Z., Ruixue, L., Xiaoli, X. et al. (2024). Construction and spatiotemporal evolution of China's new quality productivity index. *Industrial Technology and Economics*, *45*(08), 65-72. https://doi.org/10.19641/j.cnki.42-1290/f.2024.08.010

Jia, S., Jinchang, Z., & Yi, P. (2024). A study on the impact of ESG development on firms' new quality productivity--Empirical evidence from Chinese A-share listed firms. *Contemporary Economic Management. 46*(06), 1-11. DOI:10.13253/j.cnki.ddjjgl.2024.06.001.

Karacuka, M., Myovella, G., & Haucap, J. (2024). Productivity Paradox in Africa: Does Digitalization Foster Labor Productivity in African Economies? *J. Knowl. Econ*. https://doi.org/10.1007/s13132-024-02200-8

Ling, D. (2024). Theoretical Implications and Significance of Xi Jinping's Important Discourse on New Quality Productivity. *Academic Exploration*, (05), 1-8.

Loebbecke, C., & Picot, A. (2015). Reflections on societal and business model transformation arising from digitization and big data analytics: A research agenda. *Journal of Strategic Information Systems.* https://doi.org/10.1016/j.jsis.2015.08.002

Sanbao, Z., & Zhixue, Z. (2012). Regional Institutional Differences, CEO Management Autonomy and Corporate Risk Taking: Evidence from High-Tech Industries in 30 Provinces of China. *Management World*. https://doi.org/10.19744/j.cnki.11-1235/f.2012.04.009

Shuguang, X., & Jie, Y. (2018). Did executive equity incentives promote corporate upgrading-Empirical evidence from Chinese listed companies. *Nankai Management Review, 21*(03), 66-75.

Tongliang, A., Jie, W., & Xin, S. (2020). Innovation Measurement of Chinese Manufacturing Enterprises - A Cross-period Comparison Based on Micro-Innovation Survey. *China Social Science,* (03), 99-122+206.

Wang, L., & Yang, H. (2024). Digital technology innovation and corporate ESG performance: Evidence from China. *Econ. Change Restruct., 57*, 207. https://doi.org/10.1007/s10644-024-09791-x

Yongqin, W., & Wen, D. (2020). How does the rise of robots affect China's labor market? --Evidence from Listed Manufacturing Companies. *Economic Research, 55*(10), 159-175.