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Enterprise Digital Transformation: The Engine of New Quality Productivity Growth

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Abstract: In the digital age, digitalization has become an important force driving economic growth and social progress. Under the guidance of new quality productivity, future economic and social development will pay more attention to the improvement of quality and efficiency, as well as the comprehensive development of people. This article is based on data from Chinese A-share listed companies from 2012 to 2022, and explores the impact and mechanism of digital transformation on new quality productivity. The results show that digital transformation can effectively improve new quality productivity, and the conclusion has withstood a series of robustness tests. In further mechanism analysis, it is understood that digital transformation enhances new quality productivity by improving enterprise innovation efficiency and reducing information asymmetry. In addition, heterogeneity testing found that the improvement effect of enterprise digital transformation on new quality productivity is more significant in state-owned enterprises with poor internal control, loose financing constraints, and property rights attributes, providing useful insights for improving new quality productivity.

Keywords: Digital transformation, new quality productivity, innovation efficiency, information asymmetry.

1. Introduction

The arrival of the digital age marks a new stage of development for human society. Digital technology is ubiquitous and has become an important engine for promoting social development.

New quality productivity focuses on improving production efficiency, optimizing resource allocation, reducing resource consumption and environmental pollution, thereby promoting sustainable economic and social development. Zhou Wen and Xu Lingyun [1] From the perspective of political economy, it is believed that new productive forces are those generated by technological innovation as the main driving force and achieving key disruptive technological breakthroughs, which transcend traditional productive forces. In the context of the digital age, under the guidance of new quality productivity, future economic and social development will pay more attention to the improvement of quality and efficiency, as well as the all-round development of people.

Digital transformation has changed traditional production methods and management models by introducing advanced information technology and digital tools, improving production efficiency and quality, reducing production costs, and promoting the development of new productive forces, optimizing economic structure, and upgrading industries.

2. Theoretical Analysis and Research Hypothesis

Digital transformation is a key driving force for enhancing new quality productivity. By introducing advanced information technology, digital transformation not only optimizes production processes and resource allocation, improves production efficiency and resource utilization efficiency, but more importantly, it promotes technological innovation and industrial upgrading. Based on this, this article proposes:

H1: Digital transformation of enterprises can enhance new quality productivity.

In the wave of digital transformation, enterprises can utilize advanced technologies such as big data and cloud computing to provide a continuous source of power for innovation. Through digital transformation, enterprises can optimize innovation processes, achieve cross departmental and cross domain collaboration, and improve product market adaptability and competitiveness. In addition, digital transformation has also promoted the integration of enterprises and external innovation resources. With the deepening of digital transformation, enterprises will face more innovation opportunities and achieve higher quality development. Based on this, this article proposes:

H2: Enterprise digital transformation can improve innovation efficiency, thereby promoting the improvement of new quality productivity.

Before digital transformation, there were often obstacles in information communication between enterprises, consumers, and other stakeholders, leading to information asymmetry issues. And digital transformation integrates fragmented information processing by introducing advanced technologies such as big data and cloud computing, achieving rapid collection, processing, and sharing of information. This reduces the degree of information asymmetry, enabling enterprises to more accurately grasp market demand, thereby improving production efficiency and product quality, and promoting the improvement of new quality productivity. Based on this, this article proposes:

H3: Enterprise digital transformation improves new quality productivity by reducing information asymmetry.

3. Research Design

3.1. Sample selection and data source

This article explores relevant issues based on Chinese A-share listed companies from 2012 to 2022. The data is sourced from CSMAR, and the screening steps include: ①excluding financial enterprises;②Excluding ST and PT enterprises;③Remove samples with missing data;④Perform 1% truncation on continuous variables to ensure data robustness and reliability.

3.2. Model Setting

In order to test the direct impact of enterprise digital transformation on new quality productivity, this paper constructs a regression model①:

$$Npro_{i,t} = \alpha + \beta dig_{i,t} + \gamma Control_{i,t} + \mu_i + \nu_t + \varepsilon_{i,t}$$

The explained variable $Npro_{i,t}$ is new quality productivity, the core explanatory variable $dig_{i,t}$ is the enterprise digital transformation index, $Control_{i,t}$ represents the control variable, μ_i is the industry fixed effect, ν_i is the time fixed effect, and $\varepsilon_{i,t}$ is the random error term.

According to the hypothesis of this article, in order to verify how digital transformation promotes the improvement of new productivity by affecting the innovation efficiency and information asymmetry of enterprises, we conducted in-depth research in accordance with the hypothesis of this article. To test the mechanism of digital transformation on new quality productivity, the specific steps are as follows: First, construct a regression equation between digital transformation $dig_{i,t}$ and intermediary variables $M_{i,t}$, and see whether the observed regression coefficient $dig_{i,t}$ is significant; second, construct a relationship between digital transformation $dig_{i,t}$ and intermediary variables $M_{i,t}$ on new quality productivity $Npro_{i,t}$. For the regression equation of productivity, observe the significance and size of the regression coefficients of digital transformation $dig_{i,t}$ and mediating variables $M_{i,t}$ to determine whether there is a mediating effect. The specific model ② is as follows:

$$M_{i,t} = a_0 + a_1 dig_{i,t} + a_2 Control_{i,t} + \mu_i + \nu_t + \varepsilon_{i,t}$$

$$\mathrm{Npro}_{i,t} = b_0 + b_1 dig_{i,t} + b_2 M_{i,t} + b_3 Control_{i,t} + \mu_i + \nu_t + \varepsilon_{i,t}$$

In the regression model ②, the total effect of enterprise digital transformation on new quality productivity is $b_1 + a_1 \times b_2$, among which the direct effect is b_1, and when both a_1 and b_2 are significant, $a_1 \times b_2$ is the indirect effect of enterprise digital transformation on new quality productivity.

3.3. Variable measurement and description

3.3.1. Core explanatory variables

Enterprise digital transformation (dig). Many scholars have their own views and measurement methods on the degree of digital transformation. In the study of Yang Deming and Liu Yongwen [2], the expert scoring method was used to judge the degree of digital transformation of each company based on the description information of digital transformation-related keywords in the annual report, the number of disclosures, and the production and operation conditions of the company. The studies of Qi Huaijin et al. [3] and He Fan et al. [4] measured the digitalization level of the company by the proportion of the digital transformation-related part of the year-end intangible asset details disclosed in the notes to the financial reports of listed companies to the total amount of intangible assets. This paper draws on the research method of Wu Fei et al. [5] and uses Python to extract the data pool formed by the annual report text of listed companies. It searches, matches and counts the feature words related to digital transformation, and then classifies and collects the word frequencies of key technical directions to form the final total word frequencies, thereby constructing an indicator system for enterprise digital transformation, which is logarithmized to obtain an overall indicator that describes the digital transformation of enterprises.

3.3.2. Explained variable

New quality productivity (Npro). This paper draws on the research method of Song Jia et al. [6]. Based on the two-factor theory of productivity, it refines the two productivity factors, labor and production tools, and considers the role and value of the labor object in the production process. The entropy method is used to measure the new quality productivity. In order to display the results intuitively, the results are multiplied by 1000 to obtain the final new quality productivity index (Npro).

3.3.3. Intermediary variables

① Innovation efficiency (InnoEff). The number of patent applications per unit of R&D investment is used as a comprehensive indicator of innovation efficiency. The specific formula is as follows:

InnoEff = Pantent / Ln(1+R&D expenditure)

The value of Pantent is the natural logarithm of the total number of applications for invention patents, utility models and design patents plus 1. The weights of the three types of patents are determined according to 3:2:1.

② Information asymmetry (ASY). According to the construction methods of Song Min et al. [7] and Yu Wei et al. [8], three stock liquidity indicators are first constructed: the liquidity ratio indicator LR, the illiquidity ratio indicator ILL, and the yield reversal indicator GAM. The worse the stock liquidity, the higher the degree of information asymmetry; then, principal component analysis is performed on LR, ILL, and GAM to construct a comprehensive indicator of information asymmetry (ASY).

3.3.4. Control variables

A series of control variables related to company finance, growth factors, and corporate governance were selected, including company size (Size), debt to asset ratio (Lev), return on total assets (Roa), company age (Firmage), dual position (Dual), board size (Board), equity concentration (Top1), and proportion of independent directors (Indep). The specific instructions are shown in **Table 1**:

Table 1. Variable Description

Variable type	Variable Name	Variable symbols	Variable Description
Control variables	Enterprise scale	Size	Ln (total assets of the enterprise)
	Asset liability ratio	Lev	Total liabilities/total assets
	Return on total assets	Roa	Net profit/average total assets
	Enterprise age	FirmAge	Ln (inspection year - company establishment year+1)
	Integration of two positions	Dual	Chairman and management are the same person, Dual=1, otherwise 0
	Board size	Board	Ln (number of directors+1)
	Equity concentration	Top1	The largest shareholder's shareholding ratio
	Proportion of independent directors	Indep	Number of independent directors/total number of directors

4. Empirical Result Analysis

4.1. Benchmark regression

This article uses regression model ① to test the relationship between enterprise digital transformation and new quality productivity. The regression results of the direct impact of enterprise digital transformation on new quality productivity are shown in **Table 2**. The first column in the table shows the regression results that only control for industry fixed effects and year fixed effects. It shows that the relationship between digital transformation of enterprises and new quality productivity is significantly positive at a confidence level of 1%, indicating that digital transformation has a positive impact on new quality productivity. The second column shows the regression results of adding control variables at the enterprise level on the basis of the previous analysis. The results show that digital transformation of enterprises is positively correlated with new quality productivity at a significance level of 5%. The conclusion is consistent with the previous regression, supporting hypothesis 1 that digital transformation of enterprises can promote the improvement of new quality productivity.

Table 2. Benchmark regression

	(1) Npro	(2) Npro
dig	0.102^{***}	0.068^{**}
	(0.032)	(0.033)
Control variables	control	Controls
_cons	4.272^{***}	-1.040
	(0.541)	(1.088)
N	27050	27050
r2	0.057	0.061
year	control	control
industry	control	control

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

4.2. Robustness testing

4.2.1. Replace explanatory variables

This article draws on the method of Yuan Chun et al. [9] to replace the explanatory variable enterprise digital transformation indicator (dig). Firstly, by utilizing the semantic expressions of national policies related to the digital economy, a relatively complete digital dictionary is established. Then, using machine learning based text analysis method, the "Management Discussion and Analysis" (MD&A) section of the annual report of listed companies is analyzed. Finally, a comprehensive indicator reflecting the degree of digitalization of Chinese listed companies is constructed. The new measurement indicators of digital transformation were brought into the original equation for regression, and the regression results are shown in **Table 3**. It can still be concluded that digital transformation can promote the improvement of new quality productivity.

Table 3. Robustness check ①

	Npro
dig	0.229^{***}
	(0.043)
Control variables	control
_cons	-1.252
	(1.104)
N	26541
r2	0.061
year	control
industry	control

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

4.2.2. PSM inspection

To avoid possible sample selection bias, this study uses propensity score matching (PSM) for testing. This article groups the enterprise digital transformation index (dig) according to the annual industry median. If it is higher than the annual industry median, the experimental group will be considered as the enterprise with a high degree of digital transformation, while the control group will be considered as the enterprise with a low degree of digital transformation. Firstly, in this article, the control variable of Model ① is selected as the covariate, and the Logit model is used to estimate and calculate the propensity score value. Secondly, according to the nearest neighbor matching method, select 1 pair of 4 with replacement matching, and the caliper is 0.05. Finally, using the successfully matched samples for regression, **Table 4** shows that digital transformation and new quality productivity are significantly positive at a significance level of 5%, and the results are still robust.

Table 4. Robustness check ②

	Npro
dig	0.067**
	(0.033)
Control variables	control
_cons	-1.020
	(1.089)
N	27025
r2	0.061
year	control
industry	control

Standard errors in parentheses

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

5. Mechanism Identification Verification

5.1. The mediating effect of innovation efficiency

The regression results of the mediating effect of enterprise innovation efficiency are shown in **Table 5**. The first column showed a high positive correlation between digital transformation and innovation efficiency at a significance level of 1%, while the second column showed a positive effect of enterprise innovation efficiency on new quality productivity at a confidence level of 10%. Therefore, it can be concluded that enterprise digital transformation can promote the improvement of new quality productivity by improving enterprise innovation efficiency, and innovation efficiency becomes an important intermediary mechanism for digital transformation to enhance new quality productivity. Hypothesis 2 is supported.

Table 5. Mechanism testing: Innovation efficiency

	(1)	(2)
	InnoEff	Npro
dig	0.007***	0.059
	(0.000)	(0.036)
Control variables	control	control
InnoEff		0.940*
		(0.500)
_cons	-0.521***	-0.486
	(0.015)	(1.207)
N	24579	24579
r2	0.336	0.054
year	control	control
industry	control	control

Standard errors in parentheses

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

5.2. The mediating effect of information asymmetry

Table 6 shows the regression results of the mediating effect of information asymmetry. The regression results in column (1) showed a negative correlation between digital transformation and information asymmetry at a 1% significance level, indicating that as enterprises undergo digital transformation, the degree of information asymmetry can be significantly reduced. The regression results in column (2) showed that the degree of information asymmetry in enterprises is also negatively correlated with new quality productivity at a 1% significance level, indicating that reducing the degree of information asymmetry can improve new quality productivity. In summary, the digital transformation of enterprises can promote the improvement of new quality productivity by reducing information asymmetry, which is supported by hypothesis 3.

Table 6. Mechanism testing: Information asymmetry

	(1)	(2)
	ASY	Npro
dig	-0.012***	0.062*
	(0.002)	(0.033)
Control variables	control	control
ASY		-0.451***
		(0.103)
_cons	5.584***	1.503
	(0.065)	(1.235)
N	26960	26960
r2	0.557	0.062
year	control	control
industry	control	control

Standard errors in parentheses

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

6. Heterogeneity Testing

6.1. Internal control heterogeneity testing

This article divides the sample into two groups based on the annual industry median of the DiBo Internal Control Index: those with good internal control and those with poor internal control. **Table 7** shows the regression results. In the group with poor internal control, the regression result of digital transformation is significantly positive, with a significance level of 1%. However, in the group with good internal control, the regression coefficient of digital transformation on new quality productivity is not significant. This indicates that digital transformation can compensate for internal control deficiencies. Compared to enterprises with good internal control, enterprises with poor internal control have a more significant effect of digital transformation on improving new quality productivity.

Table 7. Heterogeneity testing based on internal control

	(1)	(2)
	Npro	Npro
	Good internal control	Poor internal control
dig	0.050	0.091^{***}
	(0.060)	(0.020)
Control variables	control	control
_cons	-1.083	-0.883
	(1.905)	(0.701)
N	14440	12610
r2	0.044	0.240
year	control	control
industry	control	control

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

6.2. Heterogeneity testing of financing constraints

The financing ability of a company is significantly influenced by its financial condition and credit history, which profoundly affects the pace and process of its digital transformation. This article selects the relatively robust SA index as the method of measuring financing constraints and groups them according to the annual industry median. The regression results are shown in columns (1) and (2) of **Table 8**. In the sub samples with strict financing constraints, digital transformation has no significant effect on improving new quality productivity, while in the sub samples with more relaxed financing constraints, digital transformation is highly positively correlated with new quality productivity at the 1% significance level.

Table 8. Heterogeneity testing based on financing constraints and property rights attributes

	(1)	(2)	(3)	(4)
	Npro	Npro	Npro	Npro
	Strong financing constraints	Weak financing constraints	state-owned enterprises	Non state-owned enterprises
dig	0.021	0.126^{***}	0.137^{***}	0.060
	(0.062)	(0.020)	(0.028)	(0.046)
Control variables	control	control	control	control
_cons	-2.224	-0.493	1.618^{**}	2.269
	(1.979)	(0.784)	(0.796)	(1.804)
N	13785	13265	8496	17887
r2	0.046	0.244	0.316	0.045
year	control	control	control	control
industry	control	control	control	control

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

6.3. Heterogeneity testing of property rights attributes

Compared to non-state-owned enterprises, state-owned enterprises have stronger funds and technology, and have a better foundation to achieve digital transformation.This article speculates that compared to non-state-owned enterprises, state-owned enterprises have a more significant effect in enhancing new quality productivity through digital transformation. The regression results in columns (3) and (4) of **Table 8.** Heterogeneity testing based on financing constraints and property rights attributes**Table 8** show a positive correlation between digital transformation and new quality productivity at a 1% significance level in state-owned enterprises, while in non-state-owned enterprises, the relationship between the two is not significant, which is consistent with the speculated results.

7. Conclusion and Policy Recommendations

This article is based on a large sample data and explores the impact of enterprise digital transformation on new quality productivity from both theoretical and empirical perspectives. The study found that enterprise digital transformation can promote the improvement of new quality productivity. In further mechanism analysis, it was found that digital transformation promotes the enhancement of new quality productivity by improving enterprise innovation efficiency and reducing information asymmetry. In addition, in heterogeneity testing, it was found that the improvement effect of digital transformation on new quality productivity was more significant in enterprises with poor internal control, weak financing constraints, and state-owned property attributes. Based on the research findings, the following recommendations are given:

Firstly, for the government, it should increase its support for enterprises and reduce their transformation costs through policy measures such as providing tax incentives and financial subsidies. At the same time, the government should also encourage universities, research institutions, and enterprises to cooperate and jointly cultivate digital talents to alleviate the problem of talent shortage.

Secondly, for enterprises, they should deeply recognize the importance of digital transformation, formulate clear strategic plans, and increase investment to build a sound data security protection system. In addition, strengthen communication and cooperation with supply chain partners, jointly explore new opportunities for digital transformation, and jointly enhance the competitiveness of enterprises.

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