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The Impact of Digital Transformation on Total Factor Productivity

***Peilin Li* [1, a, *], *Shaohua Cui* [1, b]**

[1] School of Finance, Henan University of Economics and Law, Zhengdong Campus, No. 180 Jinshui East Road, Zhengzhou, China

a. 2380472027@qq.com, b. 3375246446@qq.com
[*] Corresponding author

Abstract. Amid the rapid construction of a new development paradigm, digital transformation has emerged as a critical driver of social progress and economic development. This paper examines the impact of digital transformation on corporate total factor productivity (TFP) based on annual data from A-share listed companies from 2010 to 2023. The study reveals that digital transformation significantly enhances TFP, a conclusion supported by various robustness tests. Furthermore, digital transformation empowers TFP growth by reducing information asymmetry and alleviating financing constraints. Heterogeneity analysis indicates that large enterprises and highly profitable firms tend to exhibit stronger digital transformation capabilities, resulting in more pronounced TFP improvements. This study provides valuable insights for fostering new productivity dynamics and promoting high-quality corporate development.

Keywords: digital transformation, total factor productivity, information asymmetry, financing constraints

1. Introduction

In this era of rapid change, digital transformation has become a critical driving force for social progress and economic development. The report of the 20th National Congress of the Communist Party of China emphasized the need to “accelerate the construction of Digital China and promote deep integration of the digital economy with the real economy,” which not only provides a strategic direction for digital transformation but also charts a path for improving total factor productivity (TFP). According to data from the National Bureau of Statistics, China’s digital economy accounted for 42.8% of GDP in 2023, an increase of 1.3 percentage points from the previous year. The digital economy’s nominal growth rate of 7.39% exceeded the nominal GDP growth rate by 2.76 percentage points during the same period, contributing 66.45% to GDP growth and effectively supporting economic stability. This paper aims to explore how digital transformation positively impacts TFP through mechanisms such as reducing information asymmetry and alleviating financing constraints. It aligns with the spirit of the 20th National Congress report, analyzing the significance and implementation strategies of digital transformation in the context of the new era. Recent trends in digital transformation increasingly highlight its crucial role in driving enterprise innovation, enhancing competitiveness, and achieving sustainable development. With the rapid development and widespread application of technologies such as cloud computing, big data, artificial intelligence, and the Internet of Things, digital transformation has become a core component of corporate strategic planning. Through digital means, enterprises can improve production and operational efficiency, better understand customer needs, provide personalized services, and create new business models and revenue streams. Moreover, digital transformation fosters cross-sector integration and the construction of ecosystems, enabling enterprises to co-develop innovative solutions with partners from various industries, achieving value co-creation. As consumers’ expectations for digital experiences grow, enterprises must continuously optimize their digital strategies to adapt to market changes and meet user expectations.

Digital transformation has significant economic consequences, as demonstrated by existing studies. For example, He Fan and Qin Yuan [1] examined the economic outcomes of digital transformation in manufacturing enterprises driven by creativity, while Chen Xi [2] analyzed the impact of digital transformation on corporate performance. One prominent economic outcome is the significant improvement in corporate TFP. This improvement is not only reflected in the direct increase in production efficiency but also in enterprises’ ability to quickly respond to market changes, innovate, and enhance management efficiency. By integrating advanced information technology, enterprises can more effectively utilize existing resources, optimize production processes, reduce operational costs, and simultaneously stimulate employee creativity and engagement, driving the development of new products and services. Additionally, digital transformation helps enterprises better adapt to a globalized competitive environment. Through data analysis and intelligent decision-making support, enterprises can achieve more precise market positioning and risk management. Thus, digital transformation is a key factor in promoting sustainable growth and enhancing competitiveness, with profound implications for the long-term growth of TFP. The 20th National Congress report emphasized the importance of "focusing on supply-side structural reform and promoting high-quality development." Digital transformation is an essential means to achieve this goal. By leveraging digital tools, enterprises can better integrate and utilize data resources, optimize decision-making processes, and improve operational efficiency. Furthermore, digital transformation fosters the development of new business forms and models, stimulating market vitality and social creativity.

However, digital transformation is not without challenges. It requires enterprises to make corresponding adjustments and innovations in technology investment, talent development, and organizational culture. The 20th National Congress report's emphasis on "innovation-driven development" provides theoretical support and practical guidance for digital transformation. Enterprises need to actively explore digital transformation paths suitable for their development under the guidance of the Party's policies to achieve sustained TFP growth. Based on this, this paper uses annual data from China's A-share listed companies from 2010 to 2023 and employs panel regression methods to study the impact of digital transformation on TFP and explore its underlying mechanisms.

The marginal contributions of this paper are as follows: First, in terms of research content, this paper, based on micro-level data of listed companies, employs panel regression methods to study the impact of digital transformation on total factor productivity (TFP), providing a valuable supplement to micro-level research on digital transformation. Second, regarding the mechanism of action, the paper explores the impact of digital transformation on TFP from a more multidimensional perspective. It examines not only the overall effect of digital transformation on TFP but also identifies mechanisms such as R&D innovation, human capital, the integration of advanced manufacturing and modern services (hereinafter referred to as "industrial integration"), and cost reduction and efficiency enhancement. Empirical tests are conducted on these mechanisms, enriching the theoretical and empirical research on the micro-level effects of digital transformation. Third, in terms of research significance, this paper incorporates factors such as corporate micro-level characteristics and the external macroeconomic environment into its empirical analysis, exploring whether digital transformation has heterogeneous effects on the TFP of manufacturing enterprises. This provides important references for governments to formulate more precise policies. By analyzing the impact of digital transformation on TFP, this study delves into the specific pathways and mechanisms through which digital transformation affects TFP. It also reveals significant heterogeneity in the productivity-enhancing effects of digital transformation under different conditions, offering targeted references for policymakers and corporate managers.

The remainder of this paper is structured as follows: Section 2 reviews the literature and presents research hypotheses. Section 3 outlines the research design. Section 4 analyzes empirical results. Section 5 examines mechanisms. Section 6 conducts heterogeneity analysis. Section 7 concludes with recommendations.

2. Literature Review and Research Hypotheses

2.1. Research on Digital Transformation

Research on digital transformation primarily focuses on micro, meso, and macro perspectives. In terms of variable measurement, defining and quantifying digital transformation is challenging due to its subjectivity and the complex, multi-level changes involved. Digital transformation encompasses not only the application of technology but also transformations in organizational structure, corporate culture, and business models. These interrelated and mutually influencing changes make it difficult to comprehensively measure digital transformation using a single indicator or scale. Current mainstream measurement methods include Wu Fei's [3] text analysis approach, using the proportion of intangible assets in financial indicators as a proxy variable. This paper adopts the widely used text analysis method for measurement. From a macro perspective, digital transformation significantly contributes to economic growth. Chao Xiaojing and Wang Chenwei [4], in their article A Review and Prospect of the Impact of the Digital Economy on High-Quality Economic Development, conducted an in-depth analysis of how the digital economy influences high-quality economic development, covering aspects such as growth efficiency, comprehensive evaluation, and mechanisms of influence. Ge Heping and Wu Fuxiang [5] studied how the digital economy empowers high-quality economic development, including the establishment of a data-element market system and the promotion of industrial digital transformation. The State Council's 14th Five-Year Plan for the Development of China's Digital Economy [6] highlights the pivotal role of the digital economy in transforming production methods, lifestyles, and governance models while proposing specific development goals and measures. Sheng Lei [7] examined how the digital economy drives industrial high-quality development, analyzing its driving mechanisms, intrinsic logic, and implementation paths. From a meso perspective, studies on digital transformation focus on changes within industries or sectors, exploring how digitalization affects operational models, structural adjustments, and competitive strength. For instance, Qiu Zeqi et al. [8] discussed how digital transformation brings innovative paths to national governance, including its applications in the economic domain that reshape industry patterns and value chains. Li Zaichi and Lü Tie [9] found that digital transformation enhances industry flexibility, improves product quality, and reduces costs. Chen Xiaodong [10] analyzed the practical paths for the digital economy to lead industrial upgrading, including consolidating the foundation for digital economy development, promoting forward-looking digital industrialization, fostering coordinated digital industry development, and achieving industrial digitalization. Research by Liu Yang and Chen Xiaodong [11] revealed that the digital economy significantly promotes both the advancement and rationalization of industrial structures. From a micro perspective, scholars focus on how individual enterprises implement digital transformation and its impact on operations, organizational structures, market performance, and employee behavior. Existing literature primarily examines the influence of "Internet+" on corporate innovation and performance (Yang Deming and Liu Yongwen [12]; Shen Guobing and Yuan Zhengyu [13]) without constructing comprehensive indicators to reflect the extent of digital transformation at the enterprise level. Liu, Yang, and Zheng [14], in their study Index Construction and Application of Digital Transformation in the Insurance Industry: Evidence from China, developed a Digital Transformation Index System (DTII) specifically for the insurance sector. For publicly listed companies, annual reports disclose critical information about their core business activities, operational status, and management's strategic vision, offering valuable insights into corporate strategies and decision-making. Chen Qingjiang et al. [15] explored the effects of industry competition, social network embedding, and environmental uncertainty on peer effects in enterprise digital transformation. He Fan and Liu Hongxia [16] assessed the performance enhancement effects of digital transformation in traditional industries from a digital economy perspective. Therefore, this study considers constructing a digital transformation index based on annual report information from publicly listed companies.

2.2. Research on Total Factor Productivity (TFP)

Research on total factor productivity (TFP) primarily focuses on macro, meso, and micro levels. At the macro level, studies analyze TFP's contribution to economic growth and examine how macroeconomic policies influence productivity improvement. This includes exploring national-level policies on technological innovation, educational investment, and infrastructure development, as well as considering macroeconomic factors such as international trade, globalization, and technology transfer. For example, Liu Jiancui [17] conducted macro-level TFP accounting and evaluation for China, focusing particularly on environmental TFP and green TFP. Zheng Yuxin and Roski [18] studied industrial productivity during China's institutional transformation, offering insights into productivity analysis from a macroeconomic perspective. At the meso level, research emphasizes productivity within specific industries or regions, examining differences in productivity across industries and their underlying causes. Such studies analyze intra-industry technological diffusion, industrial structure, market dynamics, regional economic development models, and industrial cluster effects. For instance, Cai Hong and Xu Xiaowen [19] conducted an international comparative study on the composition of China's technological knowledge stock, examining TFP at the industry level. Similarly, Hu Angang, Zheng Yunfeng, and Gao Yuning [20] focused on the real TFP in China's high-energy-consuming industries, analyzing the impact of environmental regulations on productivity at the industry level. At the micro level, research typically centers on individual firms or industries, exploring how enterprises enhance productivity through technological innovation, management improvement, or workforce training. These studies help understand changes in firm-level production efficiency and provide strategies to improve competitiveness. For example, Chen Binkai et al. [21] explored the relationship between housing prices, resource misallocation, and the productivity of Chinese industrial enterprises, focusing on resource allocation efficiency at the firm level. Synthesizing these three levels of research offers a comprehensive understanding of TFP's dynamic changes and its impact on economic development, providing theoretical and empirical support for policymakers to develop effective economic policies.

2.3. Research Hypotheses

Enterprise digital transformation is a critical trend in modern corporate development. It not only enhances competitiveness and operational efficiency but also significantly improves customer experience, drives cultural change, and reduces operational risks. By adopting new technologies and data analytics, digital transformation enables enterprises to respond quickly to market changes, innovate products and services, optimize processes, improve decision-making, strengthen data security, and cultivate employees' digital skills. Studies have shown that digital transformation positively impacts enterprises' total factor productivity (TFP), a key metric measuring the contribution of technological progress to economic growth by accounting for the efficiency of all production factors, including capital and labor. In Digital Transformation and Total Factor Productivity: Empirical Evidence from China [22], mechanism tests demonstrate that digital transformation promotes TFP through four pathways: strengthening technological innovation, reducing operational costs, improving resource allocation efficiency, and enhancing human capital structures. As China's economy enters a "new normal," improving TFP has become a critical driver of economic growth. Digital transformation enables enterprises to utilize resources more effectively, boost production efficiency, and foster technological innovation, significantly contributing to TFP improvement across the broader economy.

Corporate digital transformation significantly reduces firms' perception of economic policy uncertainty by mitigating information asymmetry and enhancing information processing capabilities. Studies indicate that companies undergoing digital transformation, by adopting digital technologies such as artificial intelligence, big data, and cloud computing, are better able to acquire and analyze information, thereby reducing uncertainty caused by insufficient information. Furthermore, digital transformation improves resource allocation efficiency and optimizes decision-making processes, enhancing firms' adaptability to policy changes. As a result, digital transformation not only boosts corporate competitiveness and operational efficiency but also exerts a positive impact at the macroeconomic policy level, promoting improvements in total factor productivity (TFP).

Digital transformation serves as a crucial pathway for driving corporate innovation and development by effectively alleviating financing constraints and promoting TFP growth. In the current economic environment, businesses—particularly small and medium-sized enterprises—face significant challenges in accessing financing, with capital shortages being a major bottleneck for innovation activities. Digital transformation increases the transparency and accessibility of corporate information, reducing information asymmetry between firms and investors. This enables external investors to more accurately evaluate corporate value and risks, thereby improving firms' access to financing. The study Digital Transformation and Its Effect on Resource Allocation

Efficiency and Productivity in Chinese Corporations [23], using a sample of A-share listed companies in China from 2008 to 2020, empirically demonstrates how digital tools and systems help firms more effectively manage cash flows and optimize resource allocation. This reduces financing costs and ensures that limited funds are precisely channeled into innovation, research and development, and market expansion. Moreover, various government policies aimed at encouraging digital transformation, such as tax breaks, financial subsidies, and easier access to loans, directly alleviate firms' financing difficulties.

In summary, enterprise digital transformation effectively alleviates financing constraints, providing firms with greater financial support, thereby driving TFP improvement. This plays a vital role in fostering enterprise innovation, enhancing economic competitiveness, and promoting high-quality economic development.

Based on these insights, this study proposes the following hypotheses:

H1: Enterprise digital transformation enhances total factor productivity (TFP).

H2: Digital transformation improves TFP by reducing information asymmetry.

H3: Digital transformation improves TFP by alleviating financing constraints.

3. Research Design

3.1. Sample Selection and Data Sources

Given the rapid development of China's digital economy and the growing emphasis on digital applications since 2010, this paper selects annual data from A-share listed companies from 2010 to 2023 as the research sample. The data underwent the following processing: first, data from financial industries, ST and PT companies, and companies with missing data were excluded; second, key continuous variables were winsorized at the top and bottom 1%. The financial information of listed companies mainly comes from the CSMAR database, while data related to digital transformation in annual reports is sourced from the CNRDS database.

3.2. Empirical Model Construction and Variable Measurement

3.2.1. Empirical Model Construction

To explore the impact of digital transformation on firms' total factor productivity (TFP), a bidirectional fixed-effects model (1) is constructed for empirical analysis, as shown below:

$$TFP1_{i,t} = \alpha_0 + \alpha_1 DCG_{i,t} + \sum \alpha_n Controls_{i,t} + YEAR_t + IND_u + \varepsilon_{i,t} \tag{1}$$

3.2.2. Variable Measurement

3.2.2.1. Dependent Variable: Total Factor Productivity (TFP)

Scholars Lu Xiaodong and Lian Yujun [24] have utilized the LP and OP methods to calculate the total factor productivity (TFP) of listed companies. The LP method primarily addresses the endogeneity issue in estimating production functions. By using firms' investment decisions as instrumental variables, this method resolves simultaneity bias arising from the simultaneous determination of output and capital stock by firms. The LP method effectively addresses this bias while minimizing sample loss. Specifically, the algorithm for the LP method involves the following steps: first, using firms' investment as a proxy variable, it establishes the relationship between current capital stock and investment; second, the coefficients of the capital term are estimated via nonlinear least squares, ensuring consistency of the estimated coefficients across different periods.

The OP method, on the other hand, further considers the possibility of firms entering or exiting the market, thereby addressing sample selection bias. The steps of the OP algorithm are as follows: first, it establishes the relationship between current capital stock and investment and constructs an optimal investment function; second, it uses firms' investment as a proxy variable for unobservable productivity shocks to resolve simultaneity bias; third, through a two-step estimation process, it first obtains consistent and unbiased estimates for the labor term, followed by estimating the coefficients of the capital term. In the second step, a polynomial involving the logarithms of investment and capital stock is defined to represent the proxy variable, and nonlinear least squares are used to complete the estimation.

3.2.2.2. Independent Variable: Firms' Digital Transformation (DCG)

The quantitative measurement of corporate digital transformation is a cutting-edge issue in both academia and practical fields. Corporate digital transformation is a complex systematic project, and existing studies on this topic are predominantly theoretical and qualitative, as seen in works by Chen Chunhua et al. [25]. However, no unified measurement indicators for quantifying the degree of digitalization have been established. Estimating Production Functions Using Inputs to Control for Unobservables [26] focuses on estimating production functions by using firms' investment decisions and other inputs as proxy variables to control for unobserved firm-specific productivity. These proxy variables address the simultaneity bias in production function estimation. The study provides a novel method for estimating production functions, offering a more accurate reflection of firms' production efficiency and contributing significantly to understanding and improving productivity estimation methods. Drawing on the approach of Wu Fei et al. [3], this paper categorizes digital transformation into two dimensions: “underlying technology application” and “technical practice application.” “Underlying technology application” is further divided into four categories: artificial intelligence, blockchain, cloud computing, and big data. The study uses the frequency of keywords appearing in the annual reports of A-share listed companies as the original measurement standard for the degree of digital transformation. To mitigate the potential right-skewness of keyword frequency affecting regression results, logarithmic transformation of the data is also applied.

3.2.2.3. Control Variables

Referring to existing studies on corporate total factor productivity (TFP), previous scholarly research includes the following: Guo Qingwang and Jia Junxue [27] estimated China’s TFP growth rate from 1979 to 2004 using four methods, including the potential output method. Wang Jie and Liu Bin [28] developed a mathematical model to examine the relationship between environmental regulation and corporate TFP, conducting empirical tests on the impact of environmental regulation on TFP. Tang Weibing et al. [29] investigated the effects of technological innovation on TFP. Wenrong Pan and Tao Xie [30] explored the significant positive impact of digital economy development on TFP in the Chinese context, while highlighting regional differences in this effect. Based on the above research, this paper selects the following corporate characteristic variables as control variables: ownership concentration (FirstShare), ownership type (SOE), debt-to-asset ratio (Lev), Tobin’s Q (TobinQ), intangible asset ratio (Intangible), return on equity (ROE), firm size (Size), and firm age (Age). Detailed explanations of these variables are provided in Table 1.

Table 1. Variable Definitions

Variable Type	Variable Name	Variable Definition	Calculation Method
Dependent Variable	TFP1	Total Factor Productivity	TFP calculated using the LP method
Independent Variable	DCG	Degree of Digital Transformation	Logarithm of the frequency of digital transformation keywords in firms’ annual reports
Mediating Variable	FC	Financing Constraints	SA index
Control Variables	Firstshare	Ownership Concentration	Proportion of shares held by the largest shareholder
	SOE	Ownership Nature	Dummy variable: 1 for state-owned enterprises, 0 otherwise
	Lev	Leverage Ratio	Total liabilities / Total assets
	TobinQ	Tobin’s Q	Tobin’s Q value of the firm
	Intangible	Intangible Asset Ratio	Ending intangible assets / Total assets
	ROE	Return on Equity	Net profit / Average net assets
	Size	Firm Size	Logarithm of total assets at the end of the period
	Age	Firm Age	Logarithm of the firm’s age (years since establishment + 1)

3.3. (3) Descriptive Statistics

The descriptive statistics of the main variables are presented in Table 2. The average total factor productivity (TFP) of firms is 6.684, with a minimum value of 4.781 and a maximum value of 9.109, indicating an overall good productivity level among the sample firms but significant differences across firms. The average degree of digital transformation (DCG) is 1.428, with a minimum value of 0 and a maximum value of 5.142, reflecting the need for improvement in the digitalization level of Chinese firms and substantial disparities in their digital capabilities.

Table 2. Descriptive Statistics

VarName	Obs	Mean	SD	Min	Median	Max
TFP_OP	36398	6.684	0.894	4.781	6.585	9.109
TFP_LP	36398	8.325	1.069	5.990	8.232	11.180
Digital_transformationA	36398	1.428	1.417	0.000	1.099	5.142
Digital_transformationB	36398	2.919	1.272	0.000	2.890	5.858
tl	36398	0.438	0.213	0.056	0.428	0.972
cflow	36398	0.045	0.071	-0.175	0.044	0.248
tobin	36398	2.112	1.458	0.847	1.639	9.614
mbratio	36398	0.613	0.253	0.104	0.610	1.181
roa	36398	0.030	0.075	-0.357	0.034	0.204
size	36398	22.208	1.309	19.649	22.029	26.265
lnage	36398	2.199	0.780	0.693	2.303	3.367

4. Empirical Results Analysis

4.1. Baseline Regression Results

Table 3 presents the baseline regression results of the impact of digital transformation on firms' total factor productivity. Column (1) reports the regression results without control variables, showing a positive and significant coefficient of 0.074 for the degree of digital transformation at the 1% significance level. Column (2) includes additional control variables, and the coefficient for digital transformation remains positive and significant at the 1% level. This indicates that digital transformation indeed enhances firms' productivity and total factor productivity, confirming Hypothesis 1. As shown in the table, a one-standard-deviation change in digital transformation corresponds to a 1.585-standard-deviation change in total factor productivity. From an economic perspective, this demonstrates that digital transformation not only improves firms' competitiveness and market adaptability but also promotes economic structural optimization and upgrading, laying the foundation for long-term economic growth and high-quality development.

Table 3. Impact of Digital Transformation on Firms' Total Factor Productivity

	(1)	(2)
	m1	m2
VARIABLES	TFP_OP	TFP_OP
Digital_transformationA	0.074***	0.030***
	(0.007)	(0.005)
tl		0.206***
		(0.048)
cflow		0.473***
		(0.056)
tobin		-0.003
		(0.005)
mbratio		-0.250***
		(0.035)
roa		1.341***
		(0.067)
size		0.428***
		(0.013)
lnage		-0.018
		(0.017)
Constant	6.256***	-2.916***
	(0.015)	(0.267)
Observations	36,398	36,398
R-squared	0.229	0.444
Number of code	4,639	4,639
Control	YES	YES
ID FE	YES	YES
Year FE	YES	YES

Note: *10% significance level. Figures in parentheses are cluster-robust standard errors.

4.2. Robustness Tests

4.2.1. Replacing the Independent Variable (Replacing XX)

In the baseline regression analysis, this study measures the level of corporate digital transformation using text analysis, based on the frequency of keywords related to digital transformation in the annual reports of listed companies. To ensure the robustness of the empirical results, this study further adopts the method proposed by Wu Fei et al. [3], using the proportion of intangible assets related to digital transformation disclosed in the notes to financial statements relative to total intangible assets as an alternative measure of corporate digital transformation. The specific regression results are presented in Columns (1)–(2) of Table 4.

Table 4. Replacing the Independent Variable

VARIABLES	(1) TFP_OP	(2) TFP_OP
Digital_transformationB	0.095***	0.031***
	(0.008)	(0.006)
tl		0.208***
		(0.048)
cflow		0.472***
		(0.056)
tobin		-0.003
		(0.005)
mbratio		-0.250***
		(0.035)
roa		1.332***
		(0.067)
size		0.427***
		(0.013)
lnage		-0.012
		(0.017)
Constant	6.091***	-2.961***
	(0.023)	(0.270)
Observations	36,398	36,398
R-squared	0.232	0.444
Control	YES	YES
ID FE	YES	YES
Year FE	YES	YES

4.2.2. Replacing the Dependent Variable (Replacing YY)

To further ensure the robustness of the results, this study substitutes the original dependent variable with total factor productivity (TFP_OP) calculated using the OP method for robustness analysis. The specific results are shown in Columns (1)–(2) of Table 5. As shown in the table, the positive effect of digital transformation on corporate total factor productivity remains significant.

Table 5. Replacing the Dependent Variable

	(1) m1	(2) m2
VARIABLES	TFP_OLS	TFP_OLS
Digital_transformationB	0.153***	0.038***
	(0.011)	(0.006)
tl		0.270***
		(0.049)
cflow		0.660***
		(0.057)
tobin		-0.017***
		(0.006)

Table 5. Continued

mbratio		-0.304***
		(0.035)
roa		1.255***
		(0.071)
size		0.773***
		(0.014)
lnage		0.014
		(0.018)
Constant	9.669***	-6.675***
	(0.031)	(0.283)
Observations	36,398	36,398
R-squared	0.285	0.659
Control	YES	YES
ID FE	YES	YES
Year FE	YES	YES

5. Mechanism Tests

5.1. Information Asymmetry (Two-Step Method)

The previous analysis demonstrates that digital transformation can enhance total factor productivity (TFP); however, the underlying mechanism requires further investigation. This study hypothesizes that digital transformation promotes TFP by reducing information asymmetry. To test this, a two-step method is employed. The regression results, shown in Table 6, indicate that the coefficients of digital transformation are 0.007 and 0.012 before and after adding control variables, respectively, both significant at the 1% level. This suggests that digital transformation significantly enhances TFP by mitigating information asymmetry.

Table 6. Information Asymmetry

VARIABLES	(1) turnover	(2) turnover
Digital_transformationA	0.007	0.012***
	(0.004)	(0.004)
tl		0.185***
		(0.034)
cflow		0.396***
		(0.050)
tobin		0.010**
		(0.005)
mbratio		-0.105***
		(0.028)
roa		0.476***
		(0.070)
size		-0.049***
		(0.012)
lnage		0.037***
		(0.014)
Constant	0.703***	1.576***
	(0.010)	(0.249)
Observations	36,398	36,398
R-squared	0.021	0.058
Number of code	4,639	4,639
Control	YES	YES
ID FE	YES	YES
Year FE	YES	YES

5.2. Financing Constraints

The baseline regression analysis reveals the positive impact of digital transformation on TFP, but the mechanism remains unclear. To explore whether digital transformation alleviates financing constraints to improve TFP, further analysis is conducted. The specific regression results are presented in Table 7. Column (1) reports the results without control variables, showing a coefficient of -0.004 for digital transformation, significant at the 1% level. Column (2) reports the results with control variables, where the coefficient is -0.003, also significant at the 1% level. These findings suggest that firms can enhance TFP by alleviating financing constraints (Chen Zhongfei et al. [31]), supporting Hypothesis 3.

Table 7. Financing Constraints

VARIABLES	(1) SA_index	(2) SA_index
Digital_transformationA	-0.004***	-0.003**
	(0.001)	(0.001)
tl		-0.020**
		(0.009)
cflow		-0.008
		(0.012)
tobin		0.028***
		(0.003)
mbratio		0.086***
		(0.009)
roa		-0.032***
		(0.012)
Constant	-3.535***	-3.638***
	(0.003)	(0.013)
Observations	36,398	36,398
R-squared	0.806	0.824
Number of code	4,639	4,639
Control	YES	YES
ID FE	YES	YES
Year FE	YES	YES

6. Heterogeneity Analysis

6.1. Heterogeneity in Firm Size

Firm size significantly influences the degree of digital transformation. The sample firms were divided into large firms and small-to-medium enterprises (SMEs) using the median of asset size as the threshold. Columns (1) and (2) of Table 8 report the regression results on size heterogeneity. Digital transformation significantly improves total factor productivity (TFP) for both large firms and SMEs, but the effect is more pronounced in large firms. The possible reasons are as follows: compared to large firms, SMEs, as part of the "long tail" group, often struggle to obtain loans from traditional financial institutions due to insufficient collateral, directly limiting their capacity for digital investment (Nie Xiuhua and Wu Qing [32]). Under conditions of insufficient external financing, SMEs exhibit lower efficiency and quality in digital transformation than large firms. While digital transformation enhances TFP for SMEs, their limited resources, higher financing difficulties, and relatively weaker innovation capabilities often result in slower transformation progress compared to large firms. Thus, large firms demonstrate stronger digital transformation capabilities, leading to a more significant improvement in TFP.

Table 8. Firm Size Heterogeneity

	(1) High (Large)	(2) Low (Small)
VARIABLES	TFP_OP	TFP_OP
Digital_transformationA	0.021***	0.027***
	(0.006)	(0.008)
tl	0.193**	0.188***
	(0.087)	(0.057)
cflow	0.590***	0.342***

Table 8. Continued

	(0.070)	(0.075)
tobin	0.001	-0.002
	(0.006)	(0.006)
mbratio	-0.165***	-0.361***
	(0.044)	(0.049)
roa	1.717***	1.010***
	(0.106)	(0.080)
size	0.402***	0.433***
	(0.021)	(0.023)
lnage	0.057**	-0.074***
	(0.028)	(0.028)
Constant	-2.417***	-2.989***
	(0.449)	(0.457)
Observations	18,199	18,199
R-squared	0.376	0.283
Number of code	2,687	3,520
Control	YES	YES
ID FE	YES	YES
Year FE	YES	YES

6.2. Heterogeneity in Firm Profitability (ROA Grouping)

Firm profitability also significantly impacts the degree of digital transformation. The relationship between digital transformation and profitability in rural commercial banks is examined in How does digital transformation affect the profitability of rural commercial banks? [33]. Using the median profitability as the threshold, firms were categorized into high-profitability and low-to-medium profitability groups. Columns (1) and (2) of Table 9 present the regression results for profitability heterogeneity. Both high- and low-to-medium profitability firms significantly improve TFP through digital transformation, with high-profitability firms showing stronger effects. The potential reasons are as follows: high-profitability firms have greater financial resources to invest in digital transformation and are more willing to tolerate longer payback periods, as they can afford to wait for the long-term benefits of digital transformation. These firms are better positioned to attract and retain technical talent, exert greater influence within the industry, and establish stronger partnerships with technology providers and other collaborators. Additionally, high-profitability firms often cultivate a culture that encourages innovation and transformation, facilitating digital advancement. They also leverage digital transformation to solidify and expand their market position. However, this does not imply that low-to-medium profitability firms cannot achieve effective digital transformation. With government support, strategic partnerships, and innovative financing mechanisms, these firms can also realize successful digital transformation. Nonetheless, high-profitability firms demonstrate superior capabilities in this regard, leading to more pronounced TFP improvements.

Table 9. Firm Profitability Heterogeneity

	(1) (High)	(2) (Low)
VARIABLES	TFP_OP	TFP_OP
Digital_transformationA	0.016***	0.039***
	(0.006)	(0.008)
tl	0.327***	0.133**
	(0.062)	(0.064)
cflow	0.279***	0.295***
	(0.074)	(0.076)
tobin	-0.008	0.006
	(0.005)	(0.009)
mbratio	-0.104**	-0.165***
	(0.041)	(0.051)
roa	2.501***	0.794***
	(0.158)	(0.080)
size	0.415***	0.435***
	(0.016)	(0.017)
lnage	-0.001	0.070**
	(0.019)	(0.031)

Table 8. Continued

Constant	-2.800***	-3.311***
	(0.337)	(0.366)
Observations	18,199	18,199
R-squared	0.562	0.367
Number of code	4,045	3,336
Control	YES	YES
ID FE	YES	YES
Year FE	YES	YES

7. Conclusion and Recommendations

This paper first reviews the existing research on digital transformation and corporate total factor productivity (TFP) from macro, meso, and micro perspectives. Then, by constructing an empirical research model, it delves into the positive impact of digital transformation on corporate TFP and analyzes the underlying mechanisms. The main conclusions are as follows: (1) Overall, digital transformation significantly and positively impacts corporate TFP. (2) Regarding the underlying mechanisms, digital transformation improves corporate TFP by reducing information asymmetry and alleviating financing constraints. (3) Heterogeneity analysis reveals that large-scale enterprises and highly profitable firms tend to have higher degrees of digital transformation, leading to more significant improvements in TFP.

Based on the findings, the following recommendations are proposed:

7.1. For Enterprises

Research from the Institute of Industrial Economics, Chinese Academy of Social Sciences [34], highlights the growing role of the digital economy in international cooperation. The study Analysis of Financing Strategies for Digital Technology Investment under Privacy Concerns and Competition [35] further emphasizes the importance of financing strategies for digital technology investment in the face of privacy concerns and competitive pressures. Enterprises should seize the opportunities presented by the digital economy and prioritize digital transformation as a strategic focus to enhance competitiveness and productivity. Increase R&D Investment: Firms should promote technological innovation and leverage digital means to develop new products and services to enhance market competitiveness. Talent Development: Enterprises should prioritize cultivating and recruiting digital talent to support the implementation of digital transformation initiatives. Enhance Management Efficiency: By investing in digital technologies, companies can improve information systems, optimize internal management processes, and enhance decision-making efficiency, thereby boosting TFP. Employee Training: Providing training opportunities to help current employees upgrade their digital skills is essential. Monitor and Evaluate Progress: Establishing mechanisms to regularly assess the progress and impact of digital transformation and adjusting strategies as necessary can ensure alignment with transformation goals. In summary, digital transformation is a critical pathway for improving corporate TFP. Enterprises should accelerate their digital transformation efforts to achieve high-quality development by capitalizing on the opportunities brought by the digital economy.

7.2. For the Government

The government should continue to advance policies supporting digital transformation, offering policy and financial assistance, particularly to state-owned and less competitive enterprises, to promote their digital transformation. Reduce Costs for Enterprises: For firms burdened by high tax liabilities, the government can provide tax incentives and financial subsidies to lower the costs of digital transformation and encourage investment in digitalization. Comprehensive Action Plans: A detailed digital transformation action plan with clear objectives, strategies, and implementation steps should ensure systematic and coherent efforts. Industry-Specific Guidance: The government can release industry-specific digital transformation guidelines, providing tailored recommendations and best practices. The 14th Five-Year Plan for Digital Economy Development issued by the State Council [36] outlines the guiding principles, basic objectives, and development goals for China’s digital economy during the 14th Five-Year Plan period, offering policy support and directional guidance for corporate digital transformation. Moreover, the government should promote coordinated regional development in digital transformation to narrow the digital divide and achieve balanced growth.

7.3. At the National Policy Level

Digital transformation is not only an inevitable trend in economic and social development but also a vital pathway for modernizing national governance and promoting high-quality economic and social development. Infrastructure Investment: Governments and enterprises should jointly invest in building information infrastructure to enhance network coverage and service quality, providing a solid foundation for digital transformation. Public-Private Partnerships: Collaborative efforts between the government and enterprises should drive digital transformation projects, share resources and information, and ensure consistency between policies and corporate practices. Talent Development: Joint investment in digital skills and innovation capabilities is essential to improve the digital literacy of the workforce. International Collaboration: Participating in international cooperation projects, adopting advanced foreign technologies, and learning from global management practices will help enhance international competitiveness.

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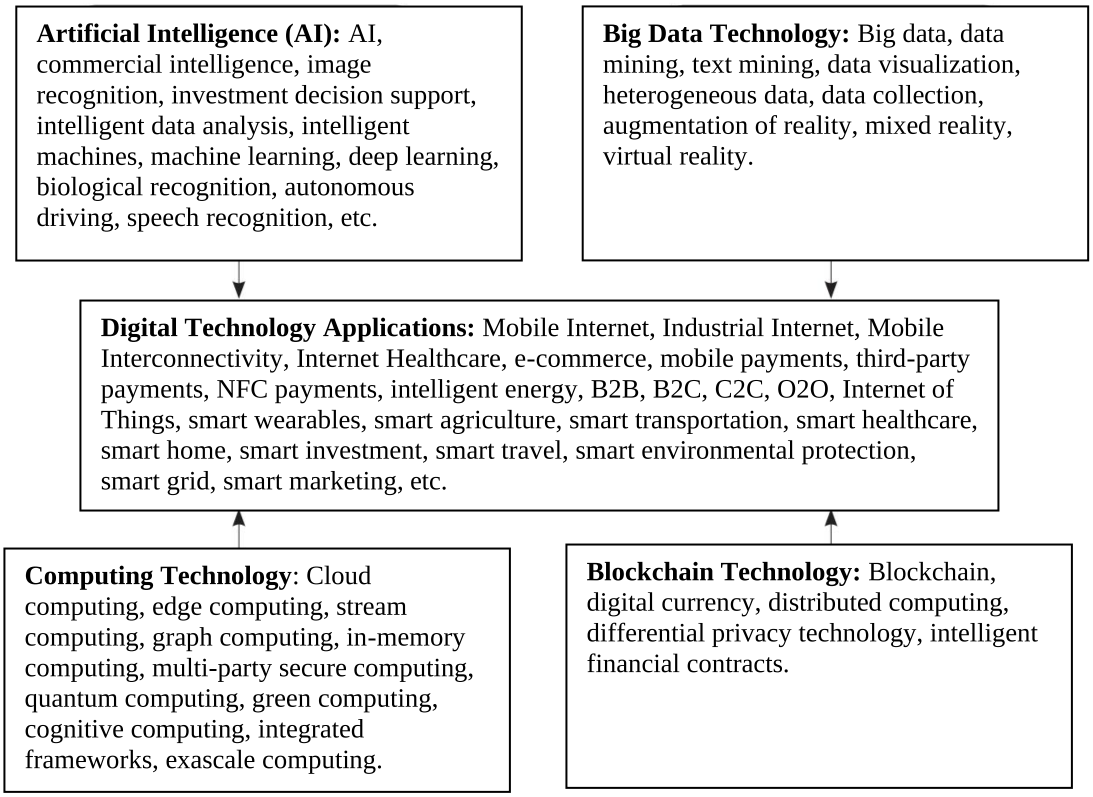
Appendix Figure 1



Appendix Table 1

Table 1. Correlation Coefficient Matrix

	TFP_OP	TFP_LP	Digital transformation A	Digital transformation B	tl	cflow	tobin	mbratio	roa	size	lnage
TFP_OP	1										
TFP_LP	0.951***	1									
Digital transformation A	0.104***	0.144***	1								
Digital transformation B	0.105***	0.160***	0.804***	1							
tl	0.371***	0.391***	-0.065***	-0.076***	1						
cflow	0.084***	0.112***	-0.024***	-0.000	-0.174***	1					
tobin	-0.285***	-0.310***	0.031***	-0.026***	-0.193***	0.063***	1				
mbratio	0.399***	0.421***	-0.064***	-0.022***	0.306***	-0.075***	-0.799***	1			

roa	0.142***	0.153***	-0.039***	-0.002	-0.372***	0.374***	0.080***	-0.115***	1		
size	0.712***	0.789***	0.065***	0.097***	0.426***	0.088***	-0.409***	0.566***	0.055***	1	
lnage	0.262***	0.265***	-0.049***	-0.121***	0.359***	-0.029***	-0.016***	0.138***	-0.182***	0.357***	1

Note: *** p<0.01, ** p<0.05, * p<0.1