Digital Transformation and Enterprise Total Factor Productivity

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Abstract. In the development era of "Internet+", digital economy, as a new economic form, has gradually become a driving force to promote the development of enterprises with high quality and high quantity. This study mainly focuses on A-share listed companies in Shanghai and Shenzhen as the research object, selects their data from 2007 to 2021, explores the impact of digital transformation on the total factor productivity from the perspective of micro-enterprises. The study finds that digital transformation can significantly increase total factor productivity, in addition to the mediating effect of technological innovation in the relationship between the two. Therefore, in the digital era, driving enterprises' digital transformation and improving their independent technological innovation capability are important channels to enhance enterprises' total factor productivity.

Keywords: Digital transformation; Technological innovation; Enterprise total factor productivity

1 Introduction

In recent years, with China's request to accelerate digital transformation and upgrading during the "14th Five-Year Plan" period, many enterprises have utilized various types of digital technology to carry out active internal governance, improve the efficiency of enterprise operations and drive enterprise value creation[1]. The role of digitization in the production and operation of enterprises is very significant, and the promotion of economic development cannot be ignored[2]. So, can digital transformation improve the total factor productivity of enterprises? If so, what means does digital technology usually drive the improvement of enterprise productivity? In this critical stage of China's economy entering the new normal, clarifying the relationship between them can give some theoretical support to the sustainable development of enterprises in the new era..

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2 Research Assumptions

With the advancement of the fourth industrial revolution, Digital economy utilizes emerging digital technology to replace traditional old kinetic energy and improve production efficiency[3]. With the extensive use of Internet technology, the information interaction ability is constantly improving, the supply and demand matching ability is optimized, which is conducive to breaking the asymmetry of market information, alleviating the output limitations caused by insufficient understanding of the demand of enterprises, facilitating the access of supply and demand sides to more effective information, improving the efficiency of the transaction, reducing the uncertainty of the market, and thus reducing the transaction costs of enterprises, thus promoting the improvement of the enterprise's production efficiency[4]. In addition, the digital economy can make time and space unrestricted through sharing, accelerate the flow of production factors among enterprises[5]. Enterprises take advantage of the interoperability of information elements, learn the advanced business model and advanced technology of leading enterprises in the industry, continuously improve self-management systems, strengthen interdepartmental collaboration, transform traditional operating methods, and realize the enhancement of enterprise total factor productivity.

H1: Digital transformation can promote the total factor productivity of enterprises.

The digital economy provides technological innovation impetus for enterprises and stimulates their independent innovation in order to improve production efficiency. Enterprises apply emerging digital technologies to traditional production methods to realize automated and intelligent production services, which reduces their innovation costs and improves innovation efficiency. Digital development accelerates the flow of information to demand-driven enterprise innovation[6]. Digital development makes the information between supply and demand gradually transparent, enterprises can access the core needs of consumers and potential demand through big data and Internet technology, and targeted innovation, timely access to consumer feedback, consumer demand side of the demand side to force enterprises to innovate[7]. The digital economy reduces the cost of enterprise innovation, reduces the risk of innovation, improves the efficiency of innovation, and enhances the total factor productivity.

H2: The development of the digital economy promotes enterprise technological innovation, which in turn enhances total factor productivity.

3 Research Design

3.1 Data sources

It mainly focuses on the A-share listed companies in Shanghai and Shenzhen as the research object, selecting their data from 2007 to 2021. The indicators of the degree of enterprises' digital transformation and total factor productivity are calculated from the relevant data of enterprises' annual reports, and the basic characteristics and financial data of enterprises are from the CSMAR database and Wind database. This paper does further screening on the basis of the original data: (1) excluding insolvency data, ST and *ST; (2) excluding the samples of the data missing samples; (3) shrinking all micro-level continuous variables by 1% and 99%. As a result of the above treatments, a total of 32,677 valid observations are obtained for 3,802 firms.

3.2 Model construction and variable definition

Explained variable

Enterprise total factor productivity (TFP), which is estimated through the LP method, in which the output index is business revenue, and the input indexes are fixed asset inputs, the number of employees in the enterprise and intermediate product inputs[8].

Core Explanatory Variables

Degree of Digital Transformation (Dig). With the help of Python crawler function to summarize the annual reports of A-share listed companies, and the text content was extracted as a data pool through the JavaPDFbox library to search, match and count the word frequency according to five dimensions, such as "Artificial Intelligence Technology, Blockchain Technology, Cloud Computing Technology, Big Data Technology, and Digital Technology Application". Based on the word frequency counts of 5 dimensions, such as "artificial intelligence technology, blockchain technology, cloud computing technology, big data technology, digital technology application", we search, match and count the word frequency counts, and construct Dig: Dig=ln (the sum of word frequency counts of the above 5 dimensions+1) [9].

Model construction

In model (1), TFP_LP is the total factor productivity calculated by LP. Following the existing literature, this paper controls for firm size (Size), gearing ratio (Lev), cashflow ratio (Cashflow), fixed asset ratio (FIXED), management expense ratio (Mfee), firm age (FirmAge), whether it is loss-making (Loss), and whether it is a state-owned enterprise (SOE) [10].

$$TFP\_LP_{i,t}=\alpha_0+\alpha_1 Dig_{i,t}+\alpha_2 Size_{i,t}+\alpha_3 Lev_{i,t}+\alpha_4 Cashflow_{i,t}+\alpha_5 FIXED_{i,t}$$
$$+\alpha_6 Mfee_{i,t}+\alpha_7 FirmAge_{i,t}+\alpha_8 Loss_{i,t}+\alpha_9 SOE_{i,t}+\mu_i+\delta_t+\varepsilon_{i,t} \quad (1)$$

Mediating effect model.

In order to further examine the mediating effect of technological innovation between digital transformation and enterprise total factor productivity, constructing a Mediation Effects Testing Process to establish a fixed effect model.

$$inv_{i,t}=\beta_0+\beta_1 Dig_{i,t}+\beta_2 Size_{i,t}+\beta_3 Lev_{i,t}+\beta_4 ROA_{i,t}+\beta_5 ROE_{i,t}+\beta_6 ATO_{i,t}$$
$$+\beta_7 Cashflow_{i,t}+\beta_8 FIXED_{i,t}+\beta_9 BM_{i,t}+\beta_{10} Mfee_{i,t}+\mu_i+\delta_t+\varepsilon_{i,t} \quad (2)$$

$$TFP\_LP_{i,t} = \gamma_0 + \gamma_1 Dig_{i,t} + \gamma_2 inv_{i,t} + \gamma_3 Size_{i,t} + \gamma_4 Lev_{i,t} + \gamma_5 ROA_{i,t} + \gamma_6 ROE_{i,t} + \gamma_7 ATO_{i,t} + \gamma_8 Cashflow_{i,t} + \gamma_9 FIXED_{i,t} + \gamma_{10} BM_{i,t} + \gamma_{11} Mfee_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \quad (3)$$

In models (2) and (3), inv is an indicator of technological innovation, which is measured by the ratio of firms' expensed R&D expenditures to total assets. The remaining control variables are: net profit margin on total assets (ROA), return on equity (ROE), total asset turnover (ATO), and book-to-market ratio (BM).

4 Empirical results and analysis

4.1 Descriptive statistics

Descriptive statistics of the main variables, as shown in Table 1:

Table 1. Descriptive statistics

variable	N	mean	p50	sd	min	max
TFP_LP	32677	8.370	8.269	1.042	6.156	11.18
dig	32677	1.201	0.693	1.357	0	4.956
Size	32677	22.18	21.99	1.283	19.88	26.21
Lev	32677	0.434	0.430	0.203	0.0570	0.886
Cashflow	32677	0.049	0.048	0.069	-0.154	0.248
FIXED	32677	0.221	0.188	0.162	0.002	0.698
Mfee	32677	0.086	0.070	0.066	0.008	0.394
FirmAge	32677	2.856	2.890	0.345	1.792	3.497
Loss	32677	0.101	0	0.301	0	1
SOE	32677	0.396	0	0.489	0	1

Table 1 shows that the mean TFP_LP is 8.370, the median is 8.269, indicating that the data results are not significantly skewed; the standard deviation is 1.042, the minimum value is 6.156, and the maximum value is 11.18, indicating that there is a certain difference in the TFP_LP between different enterprises.The mean Dig is 1.201, the median is 0.693, the minimum value is 0,,and the maximum value is 4.956, it shows that there is some variation in Dig between firms.

4.2 Benchmark regression

A fixed effects model was chosen for the regression and the results are shown in Table 2:

Table 2. Benchmark regression results

	(1)	(2)	(3)	(4)
	TFP_LP11	TFP_LP12	TFP_LP21	TFP_LP22

dig	0.106***	0.056***	0.094***	0.029***
	(24.617)	(25.285)	(26.437)	(12.500)
Size		0.508***		0.453***
		(193.567)		(115.561)
Lev		0.502***		0.243***
		(29.045)		(15.055)
Cashflow		1.190***		0.704***
		(26.556)		(25.712)
FIXED		-1.535***		-1.109***
		(-78.395)		(-53.116)
Mfee		-5.344***		-4.553***
		(-94.101)		(-108.570)
FirmAge		-0.079***		0.128***
		(-10.265)		(4.906)
Loss		-0.034***		-0.041***
		(-3.417)		(-7.044)
SOE		0.072***		-0.024*
		(11.963)		(-2.281)
_cons	8.243***	-2.243***	7.719***	-1.586***
	(1106.449)	(-38.645)	(584.897)	(-15.906)
N	32677	32677	32677	32677
adj. R^2	0.019	0.790	0.239	0.690
Year	No	No	Yes	Yes
Firm	No	No	Yes	Yes

t statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In Table 2, column (1) presents results controlling only for the Dig variable, while column (2) reports results controlling for all other variables without controlling for time and firm fixed effects. Column (3) presents results controlling only for the Dig variable and individual and year fixed effects, while column (4) reports complete results controlling for all variables. The results show that the regression coefficients of Dig and TFP_LP are significantly positive at the 1% level, as verified by HI.

From the results of columns (3) and (4), it can be seen that Dig can contribute to TFP_LP by 9.4% when other variables are not controlled, while Dig contributes to TFP_LP by 2.9% when other variables are controlled. In terms of control variables, The control variables that show a significant positive correlation with TFP_LP are firm size, gearing ratio, cash flow ratio, and year of firm establishment; the control variables that show a significant negative relationship with TFP_LP are fixed asset ratio, management expense ratio, loss-making firms, and state-owned firms.

4.3 Mediating effect

This study adds technological innovation indicators to construct a mediation effect model to further test the effect of Dig on TFP_LP. The regression results are shown in Table 3:

Table 3. Mediation mechanism test

	(1)	(2)
	inv	TFP_LP
dig	0.0007***	0.0083***
	(8.5855)	(5.3735)
inv		2.6364***
		(21.1631)
_cons	0.0460***	-4.1842***
	(12.6287)	(-61.2922)
N	26966	23485
adj. R^2	0.021	0.870
Year	Yes	Yes
Firm	Yes	Yes

t statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Column (1) reflects the regression results of model (2), adding the mediator variable of technological innovation, Dig is positive at 1% significant level, indicating that enterprise digital transformation can stimulate technological innovation. Column (2) reflects the regression results of model (3), in which technological innovation is positive at 1% significant level, indicating the existence of mediation effect, digital transformation can drive the enterprise's independent technological innovation and enhance the enterprise's total factor productivity. It verifies that H2 is valid.

4.4 Robustness test

The results of the benchmark regression have confirmed H1, but there may be an indicator selection problem that can affect the estimation results of the empirical test. For this reason, Total Factor Productivity Replacement of Explained Variables Using GMM Approach, In addition, replace and add some control variables[11]. The results are shown in Table 4:

Table 4. Robustness test results

	(1)	(2)	(3)	(4)
	TFP_GMM11	TFP_GMM12	TFP_GMM21	TFP_GMM22
dig	0.120***	0.040***	0.059***	0.025***

	(32.506)	(15.106)	(15.684)	(8.663)
_cons	3.308***	2.490***	3.149***	3.009***
	(507.491)	(32.605)	(237.345)	(27.191)
N	29409	29409	29409	29409
adj. R^2	0.037	0.609	-0.011	0.418
Year	No	No	Yes	Yes
Firm	No	No	Yes	Yes

t statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

It can be seen that the regression coefficients of Dig and TFP_GMM are significantly positive at the 1% level, saying that further validation that H1 holds true and the results underlying this study remain.

5 Conclusion and Recommendation

In today's era, digital technology is developing rapidly, and it has become an urgent need in the era of digital economy for enterprises to deeply integrate all kinds of high technology with all production factors, which is also a new path for modern enterprises to explore the development and progress of high quality and high quantity. This study empirically examined the effect of Dig on TFP, the results of the study conclude that digital transformation can lead to the growth of enterprise total factor productivity, it can lead to enterprise technological innovation, which in turn can enhance total factor productivity.

Therefore, this study proposes the following recommendations: first, vigorously develop the digital economy. Increase the research and development of digital economy industry, vigorously promote the construction of 5G communication network, improve the coverage of digital network, and improve the construction of digital technology infrastructure. Second, accelerate the digital transformation of enterprises. It need to combine digital technology with traditional business methods, improve the digital penetration rate of enterprise production and management, broaden business channels, optimize internal management, and give rise to more dynamic industries; the government should formulate reasonable policies and regulations to actively guide the digital transformation, in the meantime, enhance the new kinetic energy for the development of enterprises; and increase the support for digital inclusive finance, and alleviate the pressure of financing with financing support. Finally, enterprises need to respond to the demand situation on the consumer side, strengthen technological innovation, highly integrate the digital economy with industrial production, optimize production efficiency and improve total factor productivity.

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