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Research on the Impact of Digital Transformation on Total Factor Productivity of Manufacturing Enterprises

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Abstract

Using a dataset of Chinese A-share manufacturing listed companies from 2007 to 2022, this study constructs an enterprise digitalization index based on annual report text data and empirically investigates the impact of digital transformation on the Total Factor Productivity (TFP) of manufacturing enterprises in China. The findings reveal that digital transformation significantly enhances the TFP of manufacturing enterprises through various mechanisms, including stimulating innovative product research and development, fostering innovation capabilities, optimizing resource allocation, and upgrading human capital. Moreover, the study explores the heterogeneity of this impact across different regions and enterprise levels. It is observed that the positive effect of digital transformation is more pronounced for enterprises in the eastern region compared to those in the central and western regions. High-tech enterprises experience a more significant impact than low-tech enterprises, and the effect is more substantial for non-state-owned enterprises compared to state-owned enterprises. Additionally, the impact is more pronounced for enterprises in the growth and maturity stages than for those in the decline stage. This paper also integrates theory with practical reality, offering policy recommendations relevant to manufacturing industry.

Keywords

Digital Transformation; Total Factor Productivity; Manufacturing Enterprises.

1. Introduction

Developing new quality productive forces is a crucial strategic measure for China to gain a competitive edge against other major powers and promote high-quality development, and the core of new quality productive forces is the empowerment of factors and the improvement of total factor productivity (TFP) . In today's world, the wave of digital transformation is sweeping across various industries. As a crucial element in boosting the development of new quality productive forces, digital transformation provides manufacturing enterprises with more efficient production methods, facilitates the visualization of the production process, and enhances the efficiency of production scheduling and resource allocation. Additionally, leveraging technologies such as the Internet, cloud computing, the Internet of Things, and artificial intelligence, digital transformation increases the added value of products and creates new business models for manufacturing enterprises. The digital economy is increasingly becoming a new opportunity for a technological revolution and industrial transformation for Chinese enterprises. As the digital economy and the real economy continue to integrate and develop, the economic effects of digitalization have emerged as a significant topic. In this context, it is of great importance to study the impact of corporate digital transformation on the TFP of manufacturing enterprises.

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China's manufacturing enterprises have made significant achievements in digital transformation. On one hand, the construction of China's information infrastructure has made substantial progress, providing a robust hardware environment for the digital transformation of manufacturing enterprises. On the other hand, Chinese manufacturing enterprises have begun to actively explore the path of digital transformation through means such as intelligent manufacturing and industrial internet, thereby enhancing production efficiency, product quality, and innovation capabilities. However, Li Shuqin (2020) pointed out, through an analysis of the digital transformation of small and medium enterprises (SMEs) in the European Union, that SMEs in many countries worldwide are adopting digital means for business development, yet they face challenges and difficulties in information reception, market access, and investment acquisition during the digital transformation process. Considering China's objective reality, Chinese manufacturing enterprises still encounter numerous challenges in the process of digital transformation, such as insufficient technological R&D capabilities, talent shortages, and data security issues. Therefore, the impact and internal mechanisms of digital transformation on Chinese manufacturing enterprises require further in-depth research to provide more targeted guidance for practical operations of enterprises.

2. Theoretical Analysis and Hypothesis Formulation

The digital transformation of enterprises refers to the process by which enterprises achieve significant improvements in production and operations through the introduction of digital technologies such as big data, cloud computing, blockchain, and artificial intelligence (Lu Yanqiu et al., 2021). Existing literature primarily explores the definition of digital transformation from a technical perspective and the subsequent changes brought about by technological upgrades (Zeng Delin et al., 2021). These studies focus mainly on the downstream effects, examining the impact of digitalization on macroeconomic and microeconomic enterprises (Jing Wenjun et al., 2019; Yuan Chun et al., 2021). Jing Wenjun et al. (2019) proposed a theoretical framework for the digital economy's promotion of high-quality economic development from both micro and macro perspectives, arguing that the digital economy can provide better matching mechanisms and innovation incentives for economic production. Li Xiaohua (2019) highlighted that the digital economy is characterized by the continuous emergence of disruptive innovations, platform economy, and rapid growth, thereby providing new momentum for economic growth. Du Chuanzhong et al. (2021) studied the impact of the digital economy on enterprise productivity based on the urban digital economy index compiled by Tencent Research Institute from 2015 to 2018 and data from A-share listed companies. They identified economies of scale, economies of scope, technological innovation effects, and management efficiency effects as the intermediary mechanisms through which the digital economy exerts its influence.

This article refines the research direction by focusing on the TFP of manufacturing enterprises, using it as a key measure of the digital transformation's impact. TFP is a crucial indicator of a firm's production efficiency, capturing the contributions to output from factors beyond traditional inputs like labor and capital. These factors include technological advancements, managerial innovations, and institutional changes (Solow, 1957). Introduced by American economist Robert Solow in the 1950s, the concept of TFP has since become a central focus in both macroeconomic and business management research.

Currently, the LP (Levinsohn-Petrin) method and the OP (Olley-Pakes) method have become the mainstream approaches for measuring TFP (Yang Rudai, 2015; Ji Yunyang, 2020; Huang Xianhai et al., 2023). The highlight of the OP semi-parametric method lies in its ability to accurately correct sample selection bias and simultaneity bias using computer software. Subsequently, Levinsohn and Petrin (2003) further optimized the OP semi-parametric method,

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developing the LP semi-parametric method. The key improvement of the LP semi-parametric method is the incorporation of intermediate inputs into the calculation framework, effectively eliminating potential biases in semi-parametric estimation and thereby enhancing the accuracy of TFP measurement. Furthermore, the LP method successfully addresses the issue of zero capital inputs and the consequent sample loss associated with the OP semi-parametric method, thereby further improving the reliability of its estimation results.

Technological progress is regarded as one of the key factors for enhancing an enterprise's TFP. Chinese scholars have actively conducted research in this area. Li Ping (2016) employed stochastic frontier analysis and data envelopment analysis to estimate TFP of enterprises and investigate its influencing factors, proposing that technological progress, improvement in technical efficiency, and transformation of industrial structure are the three main pathways to enhance TFP. Cheng Chen (2017) explored the impact of differences in innovation levels on open innovation, particularly noting that innovation by a leading firm may suppress the innovation activities of other firms within the same industry, thereby hindering the improvement of their TFP. Chen Weitao et al. (2019) found that strengthening enterprise R&D activities can promote technological upgrading, thus contributing to the enhancement of TFP. Sheng Mingquan et al. (2020) emphasized that manufacturing enterprises need to engage in exploratory innovation to advance production technology, improve production efficiency, and enhance their market competitiveness.

We posit that digital transformation affects TFP of enterprises through the following mechanisms: Firstly, digital transformation enhances TFP of manufacturing enterprises by incentivizing the development of innovative products and nurturing innovation capabilities. Digital transformation enables manufacturing enterprises to better conduct innovative product development. Utilizing technologies such as big data and artificial intelligence, enterprises can quickly acquire and process market information, uncover consumer demands, and thereby target product innovation efforts to improve R&D efficiency. Additionally, digital transformation helps cultivate a company's innovation capabilities by building innovation platforms and strengthening collaboration with external innovation resources.

Secondly, digital transformation optimizes resource allocation, improving resource utilization and production efficiency, thus enhancing TFP. Digital transformation assists manufacturing enterprises in achieving optimal resource allocation. Through technologies like the Internet of Things and big data, enterprises can gain real-time insights into various aspects of the production process, enabling dynamic adjustments and optimal resource allocation to enhance resource utilization efficiency. Moreover, digital transformation promotes the automation and intelligence of production processes, thereby increasing production efficiency. For example, enterprises can implement automated production, unmanned operations, and remote monitoring through smart manufacturing systems, which reduces production costs and enhances production efficiency. Furthermore, digital transformation facilitates supply chain collaboration, optimizing supply chain management, reducing inventory costs, and improving responsiveness.

Finally, the digital transformation of enterprises enhances TFP through the upgrading of human capital. From the perspective of human capital accumulation, on one hand, the implementation of digital technologies facilitates the automation of business processes and the intelligent management of operations, prompting changes in the internal personnel structure of enterprises. This increases the proportion of multidisciplinary talents who support decision-making and management, thereby promoting the internal specialization of labor (Zhao Shukuan, 2022). On the other hand, the application of digital technologies makes it more convenient for employees to acquire and share knowledge, which helps improve their knowledge level, thus enhancing the quality and technical proficiency of human capital (Lou Runping, 2022), and consequently increasing the TFP of manufacturing enterprises.

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Therefore, based on the above analysis, this paper proposes the following hypothesis:

Hypothesis H1: Digital transformation has a positive impact on the enhancement of manufacturing enterprise's TFP.

3. Research Design

3.1. Empirical Strategy and Model Setting

Therefore, based on the above analysis, we proposes the following empirical examination to investigate the impact of digital transformation on the TFP of manufacturing enterprises:

$$TFP\_LP_{ijt} = \alpha_0 + \alpha_1 DTCG_{itj} + \varphi Controls_{ijt} + \mu_n + \theta_j + \delta_t + \varepsilon_{ijt} \quad (1)$$

Among them, TFP_LP represents the TFP which measured using the Levinsohn-Petrin (LP) method; The explanatory variable is the degree of digitalization of enterprise i in year t; Controls represent all control variables. Meanwhile, μn, θj, δt represent fixed effects in provinces, industries, and time, respectively, εijt is the residual term, and this article is also clustering the standard error to the urban level in regression.

3.2. Variable Description

3.2.1. Dependent Variable

Total Factor Productivity (TFP_LP): The total factor productivity, measured using the Levinsohn-Petrin (LP) method, is utilized as the primary dependent variable. The specific steps of the LP method are based on Lian Yujun et al. (2012), employing a semi-parametric regression approach. Intermediate inputs are used as proxy variables for external shocks, and the calculation follows a two-step estimation process grounded in the Cobb-Douglas production function:

$$lnY_{it}=\alpha_0+\alpha_1 lnK_{it}+\alpha_2 lnL_{it}+\alpha_3 lnM_{it}+\omega_{it}+\varepsilon_{it} \quad (2)$$

where Yit represents the output of firm i in year t, Kit denotes capital input, Lit represents labor input, Mit signifies intermediate input, ωit is total factor productivity, and εit is the random error term. Specifically, Yit is measured by the firm's operating revenue; Kit and Lit are measured by the firm's net fixed assets at the end of the year and the number of employees, respectively; The total cost of operations, sales, management, and financial expenses is called Mit. This amount is subtracted from depreciation and amortization as well as payments given to and on behalf of personnel.

3.2.2. Independent Variables

Nowadays, it's common practice to perform text mining on listed companies' annual reports and use keyword frequency statistics to create a digital transformation index (Sui Xiaoning et al., 2024). The majority of the literature uses the frequency of terms associated with "digitalization" as the metric. In this article, following the research of Wu Fei et al. (2021), the degree of corporate digital transformation is determined by the frequency with which terms like "artificial intelligence technology," "blockchain technology," "cloud computing technology," "big data technology," and "digital technology application" appear in the reports, followed by logarithmic transformation.

3.2.3. Control Variables

This study incorporates a total of ten control factors: firm age (age), firm size (size), cash flow (cflow), state ownership (soe), return on assets (roa), leverage (lev), proportion of intangible

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assets (itang), shareholding ratio of the largest shareholder (top1), and industry Herfindahl-Hirschman Index (HHI).

3.3. Data Sources and Explanations

This study utilizes A-share non-ST manufacturing listed companies from the the China Stock Market & Accounting Research (CSMAR) as the primary sample, covering the period from 2007 to 2022. The data were processed as follows: (1) Excluding samples of listed companies designated as ST or *ST in any year; (2) Excluding samples of companies with an asset-liability ratio greater than 1; (3) Excluding samples of companies listed in 2022 or later; (4) Deleting samples of companies with fewer than 8 employees. Additionally, the main continuous variables were winsorized at the 1% and 99% percentiles. Following these procedures, the final dataset comprises 3,280 enterprises and 28,900 observations.

Table 1. Descriptive statistics of variables

Variable type	Variable	Variable abbreviation	Variable definition	N	mean	std	min	max
Dependent variable	Total factor productivity	*TFP_LP*	Total Factor Productivity Calculated by LP Method	28000	8.260	1	4.640	11.24
independent variables	Digitization level	*DTGC*	The Digitalization Degree of Enterprises Calculated by Word Frequency Method	13398	1.680	1.260	0	5.060
control variable	Enterprise age	*age*	Ln (year - year of listing+1)	27727	2.030	0.740	0.690	3.400
	Enterprise scale	*size*	Ln(total assets)	28842	21.84	1.240	16.64	27.62
	Cash flow	*cflow*	Net cash flow generated from operating activities/total assets	28837	0.0500	0.0700	-0.170	0.350
	State owned or not	*soe*	The value for state-owned enterprises is 1, otherwise it is 0	27906	0.370	0.480	0	1
	Net profit margin of total assets	*roa*	Net profit/total assets of the enterprise	28900	0.0400	0.0600	-0.380	0.250
	Leverage	*lev*	Total liabilities/total assets	28900	0.410	0.190	0.0400	0.900
	Tobin Q value	*lntobin*	Ln (company market value/total assets)	27359	0.580	0.460	-0.190	2.390
	The proportion of intangible assets	*itang*	Net intangible assets/total assets	28900	0.0400	0.0400	0	0.260
	The largest shareholder's shareholding ratio	*top1*	Total shareholding of the largest shareholder/total share capital	28236	35.28	15.03	8.480	79.90
	Herfindahl index	*HHI*	HHI=∑ (Xj/X) 2, X=∑Xj, Among them, Xj represents the operating revenue of the j industry	26004	0.160	0.130	0.0300	1

4. Empirical Testing and Result Analysis

4.1. Analysis of Benchmark Regression Results

Firstly, we estimate equation (1) using a cross-fixed effects model to examine the impact of digital transformation on the TFP of manufacturing enterprises. This model simultaneously

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controls for province-year fixed effects, industry-year fixed effects, and province-industry fixed effects, with standard errors clustered at the city level. The results are presented in Table 2. Columns (1) to (5) show the incremental inclusion of control variables and fixed effects. The coefficients are significantly positive at the 1% level across all specifications, supporting hypothesis H1.

Table 2. Benchmark Regression Results

Variable	(1)	(2)	(3)	(4)	(5)
	TFP_LP	*TFP_LP*	*TFP_LP*	*TFP_LP*	*TFP_LP*
DTCG	0.129***	0.049***	0.043***	0.048***	0.044***
	(8.65)	(5.72)	(5.05)	(5.90)	(5.54)
Constant	8.273***	-4.830***	-4.951***	-4.928***	-5.028***
	(336.48)	(-19.18)	(-19.21)	(-12.10)	(-12.75)
Control variable	NO	YES	YES	YES	YES
Province-Year Fixed	NO	NO	YES	YES	YES
Industry-Year Fixed	NO	NO	NO	YES	YES
Province-industry Fixed	NO	NO	NO	NO	YES
N	13,054	10,660	10,589	10,539	10,515
R-squared	0.348	0.764	0.783	0.804	0.842

Note: The t-value in parentheses is calculated based on the robust standard of city clustering; *, * **** Significantly at the 10%, 5%, and 1% levels, respectively, and the following table is the same.

4.2. Robustness Check

To verify the reliability of the aforementioned logic and results, a series of robustness tests were conducted in this paper.

4.2.1. Replace the Dependent Variable

To ensure that the research conclusions are not influenced by the specific calculation methods of certain variables and to enhance the reliability of the conclusions, we employs the OP method, GMM method, OLS method, and FE method as alternatives to the LP method for calculating TFP. As shown in Table 3, no matter which method is used to calculate the TFP, digital transformation of enterprises is significantly positively correlated with TFP within the 5% level, the results are consistent with the baseline regression results, supporting hypothesis H1.

Table 3. Robustness check

Variable	Replace the dependent variable				PSM-DID	Remove some samples
	TFP_OP	*TFP_GMM*	*TFP_OLS*	*TFP_FE*		
DTCG	0.026***	0.083***	0.016**	0.013**	0.046***	0.040***
	(3.04)	(5.85)	(2.55)	(2.16)	(4.85)	(4.65)
Constant	-3.371***	-0.012	-7.097***	-7.788***	-5.128***	-4.821***
	(-10.00)	(-0.03)	(-18.68)	(-19.80)	(-12.34)	(-6.63)
Control variable	YES	YES	YES	YES	YES	YES
Province-Year Fixed	YES	YES	YES	YES	YES	YES
Industry-Year Fixed	YES	YES	YES	YES	YES	YES
Province-industry Fixed	YES	YES	YES	YES	YES	YES
N	10,515	10,515	10,515	10,515	7,445	8,507
R-squared	0.810	0.424	0.915	0.922	0.846	0.849

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4.2.2. PSM

The model may suffer from the endogeneity of omitted variables, which could be related to both the TFP of manufacturing enterprises and their digital transformation. Specifically, if the control variables in the model fail to adequately capture the differences in the degree of digitalization among enterprises, the measurement indicators of digital transformation may exhibit nonlinear effects. To address the endogeneity problem caused by omitted variables, this paper further adopts the Propensity Score Matching (PSM) method for robustness checks. In applying the PSM method, we first perform a Logit regression of the control variables on the dummy variable for digital transformation to obtain the propensity scores for each enterprise. Then, we use enterprises with the closest propensity scores as matching pairs to minimize systematic differences in initial conditions across different enterprises and reduce bias, and we use the nearest neighbor matching method (1:1) with a caliper for the matching process.

Furthermore, it is necessary to conduct a model validity test before implementing the PSM method. The results indicate no significant differences between the treatment and control groups after matching all variables. As shown in Figure 1, the absolute values of the standard deviations of all variables are basically controlled within 5%, essentially meeting the balance test assumption of PSM. The common support assumption of PSM is illustrated in Figures 2a and 2b. It can be observed that before matching, the treatment group's distribution center is higher than that of the control group; however, after matching, the distribution center of the control group shifts significantly to the right, making the distribution shape very close to that of the treatment group. Therefore, we conclude that the common support assumption of PSM is satisfied.

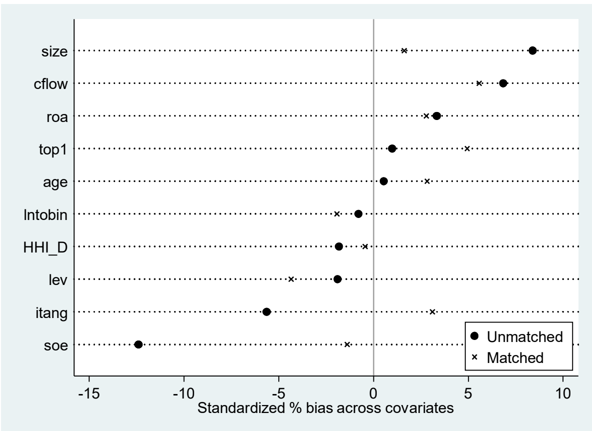

Fig. 1 Comparison of differences between the treatment group and the control group before and after PSM

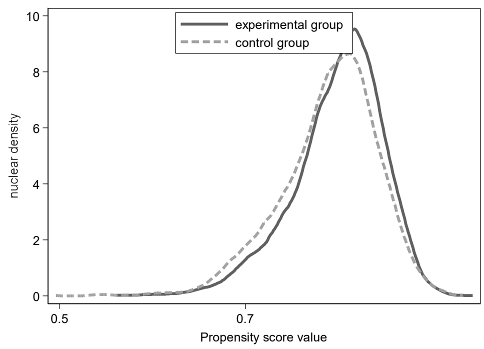

Fig. 2a Kernel density map before PSM matching

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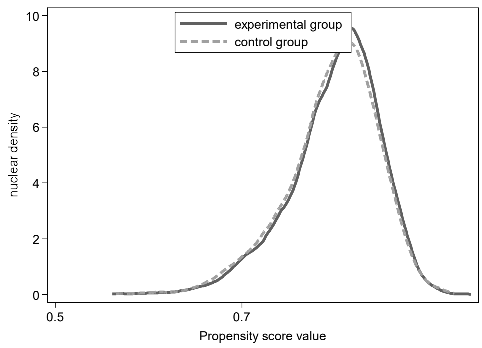

Fig. 2b Kernel density map after PSM matching

Additionally, after employs caliper nearest neighbor matching (1:1) for matching, the regression results obtained after matching are presented in Table 3, and the results indicate that digital transformation of enterprises is significantly positively correlated with TFP_LP at the 1% level, consistent with the baseline regression results. This finding supports hypothesis H1: digital transformation has a significant positive impact on the enhancement of an enterprise's TFP.

4.2.3. Remove Some Samples

Considering the unique economic and social background of the Beijing, Shanghai, and Guangzhou regions, which may result in significant differences compared to other regions, we decided to exclude samples from these regions during robustness tests to ensure the generalizability and robustness of the study results and to minimize the impact of regional differences. As shown in Table 3, the results remain consistent with the benchmark regression results, supporting hypothesis H1.

4.2.4. Instrumental Variables Method

To further mitigate the impact of endogeneity on the conclusions of this study, this section introduces an instrumental variable and employs two-stage least squares (2SLS) estimation, selecting the logarithm of urban total telecommunications services (Tele) as the instrumental variable. The selection of the instrumental variable needs to satisfy two constraints: relevance and exclusivity. First, there exists a certain correlation between urban total telecommunications services (Tele) and the degree of digital transformation. Digital technology has rapidly developed based on Teleal and telecommunication services, the increase in urban total telecommunications services may reflect improvements in information flow and logistics efficiency, which could promote digital transformation in enterprises. Thus, selecting an instrumental variable from the perspective of telecommunications services is reasonable. Second, from the perspective of exclusivity, the degree of digital transformation of enterprises is primarily influenced by their own level of innovation, and the increase in total telecommunications services itself should not directly affect the TFP of enterprises, thereby meeting the requirements of the relevance and exogeneity of the instrumental variable. The urban total telecommunications services (Tele) data used in this study is sourced from the CSMAR database.

Therefore, referring to the research of Zhao Chenyu et al. (2021), this paper selects the total telecommunications services (Tele) as the instrumental variable and applies a logarithmic transformation. The results, as shown in Table 3, indicate that the coefficients estimated using the instrumental variable method are still significantly positive at the 10% level, consistent with the baseline regression results, further verifying the robustness of the findings. supporting hypothesis H1:Digital transformation has a positive impact on the enhancement of an enterprise's TFP. Additionally, the P-values corresponding to the Kleibergen-Paap rk LM

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statistic for the dependent variable are all 0, indicating no problem of under-identification. The Kleibergen-Paap rk Wald F statistics are all greater than the critical values, rejecting the null hypothesis of "weak instrumental variables." In summary, using the logarithmic value of total telecommunications services (Tele) as an instrumental variable is justified.

Table 4. Instrumental Variables Method

Variable	(1)	(2)
	Stage 1	Stage 1
	DTCG	*TFP_LP*
IV:*Tele*	0.153***	
	(4.56)	
DTCG		0.151*
		(2.33)
Control variable	YES	YES
Province-Year Fixed	NO	NO
Industry-Year Fixed	NO	NO
Province-industry Fixed	NO	NO
Kleibergen-Paap rk LM		12.268***
Kleibergen-Paap rk Wald F		20.809
		[16.38]
N	10660	10660

Note: Values in square brackets represent the Stock-Yogo weak identification test critical values at the 10% significance level.

5. Heterogeneity Analysis

5.1. Regional Heterogeneity

To examine regional differences in the impact of digital transformation on manufacturing enterprises, the sample was divided into Eastern and Central-Western regions. Table 5 presents the regression results for each region, highlighting significant disparities. The impact of digital transformation on manufacturing enterprises in the Eastern region is significantly greater compared to those in the Central-Western region.

Several factors contribute to this disparity. First, the Eastern region is more economically developed, with enterprises possessing stronger financial capabilities and greater market competitiveness. This economic strength facilitates higher investments in digital transformation, encompassing both financial resources and talent, thereby amplifying its impact on Eastern manufacturing enterprises, companies in the Eastern region are able to adopt advanced technologies and integrate sophisticated data analytics into their operations more readily than their Central-Western counterparts.Second, the market environment in the Eastern region is more mature and competitive. Enterprises in this region face intense competitive pressures and rapidly evolving market demands, compelling them to undergo digital transformation to maintain and enhance their competitiveness. This maturity also means better infrastructure and more supportive policy environments that favor digital innovation. For example, local governments in the Eastern region often provide subsidies and incentives for technology adoption, which further accelerates digital transformation efforts. However, the Central-Western region, despite having potential, faces challenges such as limited access to capital and a less dynamic market environment.

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5.2. Technical Heterogeneity

Based on the "Industry Classification Guidelines for Listed Companies (Revised 2012)" published by the China Securities Regulatory Commission and the "High-Tech Industry Statistical Classification Directory" released by the National Bureau of Statistics, this paper classifies sample enterprises as high-tech enterprises and non-high-tech enterprises. The high-tech enterprises include the pharmaceutical manufacturing industry, special equipment manufacturing industry, railway, shipbuilding, aerospace and other transportation equipment manufacturing industries, electrical machinery and apparatus manufacturing industry, computer, communication and other electronic equipment manufacturing industries, and the instrument manufacturing industry. Other enterprises are classified as non-high-tech enterprises. A dummy variable "ind" is set, with a value of 1 for high-tech enterprises and 0 for non-high-tech enterprises.

As shown in Table 5, digital transformation has a positive impact on the TFP of both high-tech and non-high-tech enterprises, but the effect is more significant for high-tech enterprises. The possible reasons for this are as follows: High-tech enterprises typically invest more in research and development and technological innovation. Digital transformation provides more data and tools, enabling these enterprises to conduct research and innovation more effectively. High-tech enterprises can identify and respond to market changes more quickly during this process, accelerating the development and application of new products and technologies.

Table 5. Heterogeneity analysis

Variable	Regional heterogeneity			Technical heterogeneity	
	Eastern	Central	Western	Low-technical heterogeneity	High-technical heterogeneity
	TFP_LP	*TFP_LP*	*TFP_LP*	*TFP_LP*	*TFP_LP*
DTCG	0.047***	0.024	0.030	0.033***	0.048***
	(5.31)	(1.48)	(1.24)	(2.73)	(4.44)
Constant	-5.027***	-5.737***	-4.410***	-5.211***	-4.970***
	(-12.00)	(-9.85)	(-6.71)	(-11.69)	(-11.46)
Control variable	YES	YES	YES	YES	YES
Province-Year Fixed	YES	YES	YES	YES	YES
Industry-Year Fixed	YES	YES	YES	YES	YES
Province-industry Fixed	YES	YES	YES	YES	YES
N	7,769	1,523	1,039	4,644	5,711
R-squared	0.820	0.883	0.931	0.873	0.815

5.3. Heterogeneity of Enterprise Ownership

According to Table 7, digital transformation has a significant positive effect on both state-owned enterprises (SOEs) and non-state-owned enterprises (non-SOEs). From the perspective of the coefficients, the TFP of SOEs is more substantially influenced by digital transformation. However, the positive effect of digital transformation is more pronounced for non-SOEs compared to SOEs.

On one hand, SOEs, due to their unique ownership structure and management system, often have advantages in resource acquisition, policy support, and market position. These advantages enable SOEs to rapidly obtain the necessary funds, technology, and human resources needed for digital transformation, thereby achieving significant improvements in production efficiency within a relatively short period. Consequently, the larger impact of digital transformation on

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the TFP of SOEs can be attributed to their ability to fully leverage these resources and advantages during the transformation process, resulting in notable enhancements in TFP.

On the other hand, non-state-owned enterprises (non-SOEs) may exhibit relatively lower management efficiency, technological sophistication, and innovation capacity prior to digital transformation. Consequently, the improvements and advancements brought about by digital transformation are more pronounced for non-SOEs, enabling them to quickly narrow the gap with SOEs. Moreover, non-SOEs typically face more intense market competition, which compels them to be more proactive and aggressive in implementing digital transformation, thereby achieving more significant outcomes. Non-SOEs generally possess higher flexibility and adaptability in market competition. Compared to SOEs, non-SOEs have more agile organizational structures and management mechanisms, allowing them to respond more swiftly to market demands and technological changes, and to allocate resources efficiently. Therefore, digital transformation can be more rapidly implemented and effective in non-SOEs, resulting in relatively more significant positive effects.

5.4. Heterogeneity of Enterprise Lifecycle

According to the study of Liu Shiyuan et al. (2020) , the life cycle of enterprises is classified, the sample is divided into three stages: growth, maturity, and decline. The specific classification method is shown in Table 6, with data sourced from the CSMAR database.

Table 6. Combination of Cash Flow Characteristics of Enterprises at Different Life Cycle Stages

Cash flow	Growth period		Maturity period	Decline period				
	Start up period	Growth period	Maturity period	Decline period			Elimination period	
Net cash flow generated from operating activities	-	+	+	-	+	+	-	-
Net cash flow generated from investment activities	-	-	-	-	+	+	+	+
Net cash flow generated from financing activities	+	+	-	-	+	-	+	-

As shown in Table 7, the impact of digital transformation is more pronounced for enterprises in the growth and maturity stages compared to those in the decline stage. The possible reasons are as follows: Enterprises in the growth and maturity stages possess stronger resources and capabilities to support digital transformation. Growth-stage enterprises are in the phase of rapid business expansion and market share increase. They typically have significant capital investment capacity and innovation drive, enabling them to quickly adopt and implement digital technologies to enhance production efficiency and market responsiveness. Maturity-stage enterprises, although experiencing slower growth, can leverage their scale effects and accumulated market experience to invest adequate resources in digital transformation, optimizing operational processes and customer service to maintain competitive advantages. In contrast, enterprises in the decline stage face multiple challenges such as shrinking market share, resource scarcity, and internal management issues, making it difficult to mobilize sufficient funds and manpower for digital transformation in the short term. Additionally, the organizational culture of declining enterprises tends to be more conservative, with substantial resistance to change, making it challenging to swiftly adapt to the speed and innovation demands required for digital transformation.

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Table 7. Heterogeneity analysis

Variable	Heterogeneity of enterprise ownership		Heterogeneity of enterprise lifecycle		
	Non-SOEs	SOEs	Growth period	Maturity period	Decline period
	TFP_LP	*TFP_LP*	*TFP_LP*	*TFP_LP*	*TFP_LP*
DTCG	0.039***	0.068**	0.055***	0.045***	0.021
	(4.23)	(2.55)	(6.25)	(4.11)	(1.41)
Constant	-5.086***	-5.067***	-4.551***	-5.380***	-5.958***
	(-9.31)	(-8.76)	(-7.80)	(-11.11)	(-8.81)
Control variable	YES	YES	YES	YES	YES
Province-Year Fixed	YES	YES	YES	YES	YES
Industry-Year Fixed	YES	YES	YES	YES	YES
Province-industry Fixed	YES	YES	YES	YES	YES
N	7,626	2,677	4,124	3,900	1,802
R-squared	0.811	0.906	0.841	0.893	0.837

6. Conclusion and Recommendations

This article aims to investigate the effects of digital transformation on China's manufacturing enterprises from a microenterprise viewpoint, using data from A-share listed manufacturing companies in China from 2007 to 2022. Specifically, it provides empirical evidence on how digital transformation enhances the efficiency of manufacturing enterprises and promotes long-term economic development. The key findings are summarized as follows: First, digital transformation significantly increases the TFP of manufacturing enterprises. Second, it is observed that the positive effect of digital transformation is more pronounced for enterprises located in the eastern region compared to those in the central and western regions, high-tech enterprises experience a more significant impact than low-tech enterprisesand. Additionally, the impact on non-SOEs is more significant than that on SOEs, and more pronounced for enterprises in the growth and maturity stages compared to those in the decline stage.

Therefore, based on the conclusions of this paper, the following policy recommendations are proposed:

On the one hand, the government can adopt incentive measures to promote collaboration in digital transformation and facilitate the exchange of scientific research among manufacturing enterprises. For enterprises that are relatively disadvantaged in industry competition yet possess potential, preferential policies or targeted subsidies can be implemented to enhance the positive spillover effects of digital transformation. This approach aims to stimulate these enterprises' transformation and upgrading processes, thereby nurturing new productive capacities. Furthermore, the government should introduce a comprehensive set of policies, including tax incentives and research and development subsidies, to alleviate the costs associated with digital transformation, particular emphasis should be placed on enhancing support for enterprises in the central and western regions. These measures would not only incentivize technological innovation but also bolster support for the training of research personnel and the development of small digital enterprises. By fostering a conducive environment for digital advancement, such policies can significantly enhance the overall competitiveness and productivity of the manufacturing sector.

From the perspective of enterprises, advancing industrial digitalization and digital industrialization requires SOEs to take the lead. SOEs possess significant advantages in resources and capabilities, demonstrated by their long-term development and substantial investments in foundational digital technologies. Despite China’s comprehensive industrial

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system, the software and hardware essential for industrial production still rely on foreign sources. SOEs should leverage their inherent strengths by increasing investments and research efforts in critical and core technologies, addressing key "bottleneck" issues, and enhancing computational power and algorithm capabilities in fundamental digital technologies. Additionally, the integration and penetration of digitalization into other sectors should be expedited. Utilizing digital open platforms to facilitate data and knowledge sharing can promote collaborative innovation among enterprises, fostering the comprehensive high-quality development of the manufacturing sector. For non-SOEs, although some strong companies exist, many face significant challenges in the initial stages of digitalization. These challenges include substantial investment pressure, a shortage of specialized personnel, and a lack of professional databases. To overcome these hurdles, non-SOEs should actively pursue collaborations with external companies and platforms that possess advantageous resources. Through such cooperation, they can leverage mutual strengths, attract talent in digital technology, and apply these technologies to development strategies, market competition, and information collection. This approach will enable them to continuously enhance their level of digitalization and effectively utilize digital technologies.

References

[1] Zeng, Delin, Cai, Jiawei, Ouyang, Taohua. Research on Digital Transformation: Integrated Framework and Future Prospects [J]. Foreign Economics & Management, 2021, 43(05): 63-76.

[2] Li, Shuqin, Wang, Haochen, Wang, Shouyang. Comprehensive Dynamic Evaluation of Industrial Robot Development under the Background of Artificial Intelligence: A Case Study of Manufacturing Industry [J]. Systems Engineering - Theory & Practice, 2020, 40(11): 2958-2967.

[3] Lu, Yanqiu, Zhao, Bin, Song, Chang. Decision Logic, Failure Learning, and Digital Transformation Performance of Enterprises [J]. Foreign Economics & Management, 2021, 43(09): 68-82.

[4] Jing, Wenjun, Sun, Baowen. Digital Economy Promotes High-Quality Economic Development: A Theoretical Analysis Framework [J]. Economist, 2019(02): 66-73.

[5] Yuan, Chun, Xiao, Tusheng, Geng, Chunxiao, et al. Digital Transformation and Enterprise Division of Labor: Specialization or Vertical Integration [J]. China Industrial Economics, 2021(09): 137-155.

[6] Li, Haijian, Li, Zhenzhen. The Impact of Digital Transformation on High-Quality Development and High-Speed Growth of Enterprises: An Examination from the Perspective of "Quality Change, Efficiency Change, and Power Change" [J/OL]. China Rural Economy, 2024(04): 120-140.

[7] Zhao, Chenyu. Digital Development and Servitization Transformation: Empirical Evidence from Listed Manufacturing Companies [J]. Nankai Business Review, 2021, 24(02): 149-163.

[8] Zhao, Chenyu, Wang, Wenchun, Li, Xuesong. How Does Digital Transformation Affect Enterprise Total Factor Productivity [J]. Finance & Trade Economics, 2021, 42(07): 114-129.

[9] Li, Xiaoyi, Liao, Dongsheng. Tax Incentives, Supply-Side Reform, and Enterprise Upgrading [J]. Friends of Accounting, 2020(15): 48-54.

[10] Lu, Xiaodong, Lian, Yujun. Estimation of Total Factor Productivity of Chinese Industrial Enterprises: 1999–2007 [J]. China Economic Quarterly, 2012, 11(02): 541-558.

[11] Chu, Haoyu. Study on the Impact of Digital Economy on the Total Factor Productivity of Manufacturing Industry [D]. Nanjing University of Finance and Economics, 2024.

[12] Zhou, Donghua, Wan, Yijian. Can Enterprise Digitalization Improve Total Factor Productivity [J]. Statistical Research, 2023, 40(12): 106-118.

[13] Liu, Shiyuan, Lin, Zhifan, Leng, Zhipeng. Has Tax Incentive Improved Enterprise Innovation Level? A Test Based on Enterprise Life Cycle Theory [J]. Economic Research Journal, 2020, 55(06): 105-121.

[14] Du, Yong, Lou, Jing. The Impact and Spillover Effect of Digital Transformation on Enterprise Upgrading [J]. Journal of Zhongnan University of Economics and Law, 2022(05): 119-133.

[15] Wang, Jingbin, Liu, Zhaoning, Liu, Xinmin. Digital Transformation and Enterprise Total Factor Productivity: A Mechanism Test Based on Resource Allocation Efficiency [J]. Science & Technology Progress and Policy, 2024, 41(03): 23-33.

[16] Cai, Qingfeng, Wang, Hanyu, Li, Dongxu. Internet Loans, Labor Productivity, and Enterprise Transformation: From the Perspective of Labor Mobility [J]. China Industrial Economics, 2021(12): 146-165.

[17] Li, Xiaohua. New Characteristics of Digital Economy and Formation Mechanism of New Momentum for Digital Economy [J]. Reform, 2019(11): 40-51.

[18] Du, Chuanzhong, Zhang, Yuan. Research on the Impact Mechanism of Digital Economy Development on Enterprise Productivity Growth [J]. Securities Market Herald, 2021(02): 41-51.

[19] Li, Ping. Paths and Influencing Factors for Enhancing Total Factor Productivity: A Review from the Perspective of Growth Accounting and Frontier Decomposition [J]. Management World, 2016(09): 1-11.

[20] Chen, Weitao, Han, Feng, Zhang, Guofeng. Internet E-commerce, Enterprise R&D, and Total Factor Productivity [J]. Nankai Economic Studies, 2019(05): 41-59.

[21] Wu, Fei, Hu, Huizhi, Lin, Huiyan, et al. Enterprise Digital Transformation and Capital Market Performance: Empirical Evidence from Stock Liquidity [J]. Management World, 2021, 37(07): 130-144+10.

[22] Wu, Fei, Chang, Xi, Ren, Xiaoyi. Government-Driven Innovation: Fiscal Science and Technology Expenditure and Enterprise Digital Transformation [J]. Fiscal Research, 2021(01): 102-115.

[23] Dong, Hua, Sui, Xiaoning. Research on the Path of Service-Oriented Transformation of Manufacturing Enterprises Driven by Digitalization: A Theoretical Analysis Based on DIKW [J]. Modernization of Management, 2021, 41(05): 72-76.

[24] Cheng, Chen. Technological Innovation Spillovers and Enterprise Total Factor Productivity: An Empirical Study Based on Listed Companies [J]. Economic Science, 2017(06): 72-86.

[25] Sheng, Mingquan, Wu, Shaomin, Zhang, Yanan. Exploratory Innovation and Enterprise Total Factor Productivity [J]. Industrial Economics Research, 2020(01): 28-41.

[26] Du, Chuanzhong, Guan, Haifeng. Digital Economy and the Technological Complexity of China's Manufacturing Exports: A Test Based on Mediation and Threshold Effects [J]. South China Journal of Economics, 2021(12): 1-20.

[27] Yang, Rudai. Research on Total Factor Productivity of Chinese Manufacturing Enterprises [J]. Economic Research Journal, 2015, 50(02): 61-74.

[28] Huang, Xianhai, Dang, Boyuan, Song, Anan, et al. Digital-Driven High-Quality Development of China’s Strategic Emerging Industries under the New Development Pattern [J]. Economist, 2023(01): 77-86.

[29] Huang, Xianhai, Yu, Liuming, Yuan, Yiming. Industrial Robots and Enterprise Innovation: From the Perspective of Human Capital [J]. Studies in Science of Science, 2023, 41(02): 356-368.

[30] Ji, Yunyang, Gao, Yue. Modernization of Tax Governance and Enterprise Total Factor Productivity: Research Based on Quasi-Natural Experiments of Enterprise Tax Credit Ratings [J]. Journal of Finance and Economics, 2020, 46(12): 49-63.

[31] James Levinsohn and Amil Petrin. Estimating Production Functions Using Inputs to Control for Unobservables[J]. The Review of Economic Studies, 2003, 70(2) : 317-341.

[32] Jacobson,L. S.,LaLonde,R. J. and Sullivan,D. G.,1993,“Earnings Losses of Displaced Workers”,The American Economic RevR&Dw,83(4),pp.685-709.

[33] Solow Robert M. "book-review"Productivity and Technical Change[J]. The Review of Economics and Statistics, 1962, 44(4) : 501-502.

[34] Cash Flow Patterns as a Proxy for Firm Life Cycle[J]. The Accounting Review, 2011, 86(6) : 1969-1994.

[35] Kun-Huang Huarng and Tiffany Hui-Kuang Yu. Entrepreneurship, process innovation and value creation by a non-profit SME[J]. Management Decision, 2011, 49(2) : 284-2.