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Article

The Impact of Digital Technology on Total Factor Productivity in Manufacturing Enterprises

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Abstract: Digital technology drives high-quality development in manufacturing while serving as a critical enabler for advancing the digital economy. Using data from the Chinese list of manufacturing enterprises from 2012 to 2023, this study empirically analyzes the impact of digital technology on total factor productivity (TFP) in manufacturing and its mechanism of action and further explores its heterogeneity. The results show that digital technology has significantly promoted total factor productivity in manufacturing; this effect was still valid after a series of robustness tests and endogeneity tests were conducted. The mechanism analysis indicated that digital technology enhances total factor productivity in the manufacturing enterprises through the enhancement of the innovation ability of enterprises and the reduction in the operation and management costs. The heterogeneity analysis showed that digital technology has a more significant effect on the total factor productivity enhancement of enterprises in the eastern region, state-owned enterprises, and small and medium-sized enterprises. The conclusions provide clear policy implications for the promotion of the digital transformation of enterprises, accelerating the formation of high-quality productivity in enterprises, and promoting the high-quality development of the manufacturing industry.

Keywords: digital technology; total factor productivity; manufacturing; innovation ability; operation management costs

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1. Introduction

In the context of the current global economic transition, the manufacturing industry's development model is significantly impacted by the rapid development of digital technologies; consequently, there is great potential for improvement in total factor productivity. The application of digital technologies not only optimizes production processes but also drives industrial upgrading and enhances the competitiveness of enterprises. With the continuous iteration of cutting-edge technologies, such as 5G, artificial intelligence, cloud computing, and blockchain, digital technologies have brought new opportunities for productivity enhancement in the manufacturing industry, providing significant momentum for the achievement of high-quality development [1]. The Chinese government has explicitly emphasized the need to cultivate growth momentum for the next generation of information technologies to promote the deep integration of the digital economy with the real economy. This highlights the critical role of digital technologies in improving economic efficiency and driving industrial transformation.

As the cornerstone of the national economy, the improvement of total factor productivity in the manufacturing industry is of critical significance for overall economic growth. The widespread application of digital technologies has enabled the manufacturing industry to achieve more efficient resource allocation and production process optimization, thereby enhancing productivity [2]. For example, the application of smart manufacturing and automation technologies has efficiently utilized human and material resources in the production process, reduced operational costs, and

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increased flexibility. Meanwhile, the combination of data analytics and artificial intelligence enables enterprises to monitor production status in real time, forecast market demand, and optimize inventory management, further enhancing total factor productivity. However, continuous investment in information technology does not always translate into total factor productivity growth, as evidenced by the "mismatch" between IT investment and productivity in some regions, which is known as the "Solow Paradox" [3]. This paradox is particularly pronounced in China's economic transformation, where the manufacturing industry urgently needs to leverage digital technologies to enhance production efficiency and optimize the industrial structure to address the increasingly severe competitive challenges, thereby achieving the goals of sustainable development and innovation-driven growth.

Therefore, studying the impact of digital technologies on the total factor productivity of the manufacturing industry helps to create an understanding of their enabling role and provides theoretical support and policy insights that promote the deep integration of the digital economy with the real economy. This research not only holds significant theoretical value but also offers new perspectives and directions for China's manufacturing industry to achieve high-quality development under the new economic conditions. By exploring how digital technologies enhance enterprise productivity, this research supports China's economic transition and upgrade toward higher quality.

This study's possible contributions to the existing literature focus on several aspects of digitalization. First, from a theoretical perspective, this study enriches and extends the understanding of the internal mechanisms through which digitalization influences industrial development. By employing microlevel data from listed manufacturing firms and conducting empirical analyses, it provides a novel perspective on how digital technologies empower the manufacturing industry. Second, this study examines the direct impact of digital technology on total factor productivity in manufacturing and explores the mediating roles of corporate innovation capabilities and operational management costs. It reveals how digital technology indirectly enhances productivity by fostering innovation and optimizing cost management and provides targeted references for policymaking and corporate practices. Finally, this study further examines how firm size, ownership characteristics, and regional economic development levels moderate the impact of digital technology on total factor productivity. By revealing the heterogeneity in its application effects, this research provides detailed empirical evidence to support the promotion of digital technology and the development of targeted regional policies.

2. Literature Review

Research on the relationship between digital technologies and total factor productivity in the manufacturing industry is still in the exploratory stage. The existing studies have different perspectives and views on this topic mainly focus on the following three aspects.

Firstly, from the perspective of production factor synergy, digital technology is viewed as an expansionary production factor technology. Acemoglu and Restrepo (2018) propose that digital technologies are regarded as applied technologies for realizing intelligent production and are primarily characterized by their substitutive effect on labor [4]. Within this framework, digital technologies not only improve production efficiency but also trigger profound transformations in the structure of the labor market. Hammershøj (2019) contends that digital technologies serve as crucial auxiliary tools for boosting production efficiency by optimizing the structural relationship between capital and labor, usually without significantly affecting market share [5]. Bai et al. (2024) emphasize that the prominent efficiency-enhancing effects of digital technologies hinge on their interaction with traditional production factors, driving improvements in production efficiency while also boosting the overall innovation capacity of enterprises [6]. Furthermore, Cheng et al. (2023) emphasize the dividend effect of digital technologies, stating that once integrated into the production factor system, digital technologies can significantly enhance the efficiency of resource allocation [7]. This synergistic effect not only provides a competitive advantage for enterprises but

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also lays the foundation for the efficient operation of the manufacturing industry. In the current economic climate, manufacturing firms must prioritize the integration and application of digital technologies, leveraging smart and digital transformations to optimize production processes and management models.

Secondly, from the perspective of factor productivity improvement, it is believed that digital technology can enhance product quality and added value. Liu and Zuo (2025) found through empirical research that the intelligent transformation of the manufacturing industry significantly promotes the growth of total factor productivity (TFP). This suggests that technological advances have boosted overall economic growth while improving production efficiency [8]. Baratta et al. (2024) point out that the use of industrial robots in the manufacturing industry contributes significantly to productivity improvement, showing the effect of digital technology in reducing labor intensity and improving productivity [9]. Makridakis (2017) points out that digital technology can identify potential production bottlenecks through predictive analytics; this enables companies to take measures in advance, thus avoiding losses and enabling employees to more efficiently complete their tasks; consequently, labor productivity is fundamentally improved [10]. Lokuge et al. (2025) argue that the application of digital technology in enterprises improves capital productivity by optimizing production processes, and they contend that automation and intelligent management enhance production capacity and responsiveness to produce higher outputs per unit of capital, thus significantly enhancing the efficiency of capital inputs [11]. In addition, Kromann et al. (2020) point out that digital tools such as artificial intelligence and machine learning, through the combination of human–machine collaboration and deep learning, help enterprises to predict market demand, optimize inventory management, ensure efficient use of resources, and significantly improve labor productivity and management effectiveness [12].

Thirdly, from the perspective of the productivity paradox, it is suggested that digital technology may inhibit the growth of total factor productivity. Torrent-Sellens (2024) argues that when digital technology is mismatched with local infrastructure or economic conditions, its integration may lead to the “hollowing out” of the economic structure, thereby failing to effectively promote economic growth [13]. Xin et al. (2023) point out that although the digital economy has transformed the modes of social production within national economies and offered more efficient economic operation models, the GDP and total factor productivity growth in many countries have not been as significant as expected in recent years [14]. This indicates that, in certain cases, the introduction of digital technology has not effectively translated into tangible economic benefits. Bonsay et al. (2021). similarly argue that the application of artificial intelligence technology has a highly complex impact on TFP, with excessive reliance on intelligent technologies potentially leading to a decrease in TFP [15]. Siddik et al. (2025) conducted an in-depth analysis of the impact of digital technology on total factor productivity (TFP), highlighting that this impact often exhibits a delayed effect and may not directly drive TFP growth in the short term [16]. This suggests that, in the initial stages, enterprises may fail to fully recognize the potential of digital technologies, leading to either overestimation or underestimation of their effects. Meanwhile, Brynjolfsson et al. (1998) proposed that measurement errors are one of the key factors contributing to the productivity paradox, as traditional accounting methods often fail to adequately account for the benefits derived from information technology capital [17]. This measurement error not only obscures the potential contributions of digital technologies to productivity enhancement but also leads to misunderstandings among academics and policymakers about their utility.

In recent years, the Chinese government has placed great emphasis on the development of the digital economy; it has continuously promoted the deep integration of digital technologies with the real economy, and the construction of a digital China has been elevated to a national strategic goal. Zhao et al. (2024) point out that digital technologies are not only new engines driving the growth of total factor productivity in the manufacturing industry but also core drivers of high-quality development in the sector [18]. Therefore, leveraging digital technologies to enhance total factor productivity in manufacturing enterprises has become a significant trend for future development.

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The exploratory studies by domestic and international scholars provide important insights for this study; however, some limitations remain. Currently, the intrinsic connection between digital technologies and the growth of total factor productivity in the manufacturing industry remains unclear, and the specific pathways through which digital technologies enhance total factor productivity have not been thoroughly explored. To address this, this study uses panel data from A-share listed manufacturing firms in China from 2010 to 2022; text analysis is employed to measure the digital technology level of manufacturing enterprises, and the impact of digital technology on total factor productivity in the manufacturing industry is empirically tested. The study also examines the mechanisms through which corporate innovation capacity and operational management costs affect total factor productivity, and it further explores the heterogeneity of digital technology's impact. It aims to gain a deeper understanding of the critical role and complexity of digital technology in enhancing productivity in the manufacturing industry.

3. Theoretical Analysis and Hypotheses

3.1. The Impact of Digital Technology on Total Factor Productivity in Manufacturing

Digital technologies have injected substantial momentum into the manufacturing industry, significantly enhancing its performance in terms of total factor productivity. Through the deep integration of big data management and its application, digital technologies have optimized the value network structure of the manufacturing industry, thereby stimulating corporate creativity [19]. The digital transformation of enterprises has accelerated the incubation process of new products and services, expanded the boundaries of production activities, and comprehensively enhanced the manufacturing industry's production efficiency and market competitiveness. Meanwhile, digital technologies, with their powerful data processing and mining capabilities, have effectively unlocked the economic value of vast amounts of internal and external data within enterprises [20]. Based on these deeply analyzed data, enterprises can achieve precise control and optimal allocation of resource inputs and production processes, thereby enhancing operational strategies and production decisions. Furthermore, technological advancements driven by digital technologies have fostered specialization and efficient collaboration within the manufacturing industry, shifting the division of labor from traditional inter-industry to more refined intra-product levels; these advancements extend to the full lifecycle management of complex technological products across countries [21]. This cross-sector collaboration enhances inter-industry division efficiency while generating significant digital–physical integration effects through resource integration and platform optimization, thereby improving overall industry efficiency and breaking traditional production boundaries to drive the optimization and upgrading of the manufacturing sector's industrial structure [22]. In the context of the thriving digital economy, the use of data, as an emerging production factor, has been deeply integrated into every aspect of value creation within enterprises. The ability to accurately acquire and analyze data has become a crucial tool for enterprises to make informed decisions and seize market opportunities [23]. More importantly, digital technologies have significantly enhanced computational power, enabling the rapid flow of data and the deep analysis of vast amounts of information, thereby alleviating information asymmetry, optimizing internal processes, and driving a substantial improvement in overall productivity [24]. Therefore, this study proposes the following hypothesis:

Hypothesis H1: Digital technology can promote total factor productivity improvement in the manufacturing industry.

3.2. Analysis of the Impact Mechanism of Digital Technologies on Total Factor Productivity in the Manufacturing Industry

3.2.1. Enterprise Innovation Capacity

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Digital technology can enhance the total factor productivity of the manufacturing industry by enhancing the innovation ability of enterprises; this ability is manifested in the following ways. First, digital technologies have been deeply integrated into various aspects of enterprises, including research and development, production, supply chains, and markets, enabling coordinated development both within enterprises and across inter-enterprise networks [25]. By leveraging technologies such as big data, cloud computing, and artificial intelligence, enterprises can more accurately capture market demand, optimize innovation processes, and enhance resource allocation efficiency. Through in-depth analysis of consumer data and behavioral data, enterprises can launch personalized and customized innovative products to meet the diverse demands of the market [26]. Second, digital technologies have eliminated geographical barriers between enterprises and users, enabling enterprises to involve users in the innovation process on a broader scale [27]. Through digital platforms, users can participate in various stages, such as product design, improvement, and feedback, and become an integral part of enterprise innovation. This user-participation innovation model not only enhances the innovation capabilities of enterprises but also increases user loyalty and satisfaction [28]. Digital technologies have created opportunities for the manufacturing industry by enhancing its innovation capabilities and enabling dynamic tracking of the innovation process, thereby directly contributing to the improvement of total factor productivity. Third, the deep integration of digital technologies and enterprise innovation has driven technological advancements and industrial upgrading in the manufacturing sector [29]. Digital technologies not only spark the emergence of more innovative ideas but also attract global innovation resources and talent by establishing innovation platforms, jointly driving technological innovation within enterprises. In addition, the deep integration of digital technologies with non-digital physical products has given rise to disruptive innovative products, driving the transformation and upgrading of the manufacturing industry. Therefore, this study proposes the following hypothesis:

Hypothesis H2: Digital technology can promote the total factor productivity of the manufacturing industry.

3.2.2. Operational Management Costs

Digital technology can promote the improvement of total factor productivity in the manufacturing industry by reducing operational and management costs, which can be explored in terms of both operational efficiency and management costs. In terms of operational efficiency, digital technologies have significantly enhanced the production and operational capabilities of enterprises. By intelligently upgrading existing production equipment, enterprises can achieve real-time monitoring of equipment performance and conduct in-depth analyses of production data, which result in reduced maintenance costs and significantly improved operational efficiency [30]. The application of digital management systems enables the rapid flow of information, allowing real-time coordination across various stages and preventing the resource waste caused by information delays. Through a series of intelligent and digital measures, the operational management model of enterprises has become more efficient, thereby reducing overall operational costs and improving total factor productivity [31]. In terms of management costs, digital technologies also play a crucial role. By leveraging cutting-edge digital technologies such as artificial intelligence, big data, and the Internet of Things, enterprises can achieve refined management of the entire product lifecycle, from design to disposal, ensuring high transparency and traceability of information, thereby greatly enhancing management accuracy and efficiency [32]. This precise management not only reduces the complexity of internal control but also lowers labor and time costs. The application of digital technologies has facilitated the flattening of internal management structures, making information transmission faster and more efficient and reducing coordination costs between organizations [33]. The new management model improves decision-making efficiency, allowing enterprises to maintain flexibility and adaptability in a rapidly changing market environment. In addition, digital technologies optimize supply chain management

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through the integration and consolidation of resources, ensuring precise alignment between production and market demand and effectively avoiding inventory buildup and resource wastage [34]. Therefore, the application of digital technologies not only reduces operational management costs but also provides strong support for the improvement of total factor productivity in the manufacturing industry. By enhancing operational and management efficiency, digital technologies enable enterprises to gain a competitive edge in the intense market competition and to achieve sustainable development. Therefore, this study proposes the following hypothesis:

Hypothesis H3: Digital technology can promote the total factor productivity of the manufacturing industry by reducing operation and management costs.

4. Research Design

4.1. Variable Definition

4.1.1. Total Factor Productivity

There are various methods for calculating an enterprise's total factor productivity (TFP). This study follows the approaches of Chen (2024) [35] and Liu et al. (2023) [36] by using the OP to calculate TFP at the microlevel. Compared to other methods, the OP method can better mitigate the sample selection and endogeneity problems in traditional measures, thus improving the accuracy of firm productivity measurement.

4.1.2. Digital Technology

With reference to Yu et al. (2024) [37] and Luo et al. (2025) [38], this study takes the frequency of specific keywords in the annual reports of listed companies as a proxy variable for the degree of digital technology (Dig) of the listed companies. We use Python to capture 10 keywords concerning digital technology, such as big data, blockchain, artificial intelligence, and cloud computing, as proposed by Luo, et al. [38], who investigated word frequency statistics in the texts of the annual reports of A-share listed companies. The keyword frequencies are processed by adding 1 and taking the natural logarithm to obtain an index of the digital technology of enterprises.

4.1.3. Mediating Variables

(1) Enterprise innovation capability (Rd), with reference to the study by Li et al. (2022) [39]: this study adopts the logarithmic value of the R&D capital investment of manufacturing firms to measure corporate innovation capability.

(2) Operation and management cost (Cost), with reference to the study by Chen et al. (2024) [40]: this study adopts the cost/expense ratio to measure the operation and management cost of manufacturing enterprises. The larger this indicator, the higher the operation and management cost of the enterprise.

4.1.4. Control Variables

According to the existing research, the factors influencing total factor productivity in the manufacturing industry are diverse. Following the studies by Qi et al. (2024) [40], Wei et al. (2024) [41], and Zhang & Zhang (2024) [42], this study selects the following control variables: enterprise age (Age), enterprise size (Size), Leverage ratio (Leve), return on assets (Roa), level of cash holdings (Cash), board size (Board), equity concentration (Fist), and combined title of board chair and CEO (Dual). The variables involved in this paper are shown in Table 1.

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Table 1. Explanations of variables.

Type	Variable	Symbol	Method of Calculation
Explained Variable	Total Factor Productivity	TFP	OP method for calculating total factor productivity in manufacturing
Explanatory Variable	Digit technology	Dig	Ln(words keywords related to digital technology+1)
Mediating Variables	Enterprise innovation capacity	Rd	Logarithmic value of firms' R&D investment costs
	Operational Management Costs	Cost	Operating costs and administrative expenses/Total income
Control Variables	enterprise age	Age	ln(Observation year - Year of establishment+1)
	Firm Size	Size	ln(Total assets at the end of the year)
	Leverage ratio	Leve	Dept/Total assets
	Return on assets	Roa	Net profit/Total assets
	level of cash holdings	Cash	Cash/Total assets
	Board size	Board	Total number of board members
	Equity concentration	Fist	The greatest shareholder's percentage of the total shares
	Combined title of board chair and CEO	Dual	Whether the chairman of the board of directors is also the general manager

4.2. Model Specification

Based on the theoretical analysis above, this study examines the direct impact of digital technology on the total factor productivity of the manufacturing enterprises. The benchmark model was established as follows:

$$TFP_{it}=\beta_0+\beta_1 Dig_{it}+\beta_2 Controls+Ind_j+Pro_k+Year_t+\varepsilon_{it} \quad (1)$$

To further examine the mechanism through which digital technology impacts the total factor productivity of manufacturing enterprises, we constructed the following mediating effects models:

$$MV_{it}=\beta_0+\beta_1 Dig_{it}+\beta_2 Controls+Ind_j+Pro_k+Year_t+\varepsilon_{it} \quad (2)$$

$$TFP_{it}=\beta_0+\beta_1 Dig_{it}+\beta_2 MV_{it}+\beta_3 Controls+Ind_j+Pro_k+Year_t+\varepsilon_{it} \quad (3)$$

where the subscripts i, j, k, and t represent enterprises, industries, provinces, and years, respectively. TFP is the total factor productivity of the manufacturing enterprises, Dig is the level of digital technology of the enterprises, and Controls is a series of control variables. MV is the mediating variable, which is the innovation capacity of the enterprises and the operation and management costs. Ind, Pro, and Year represent industry fixed effects, province fixed effects, and year fixed effects, respectively. ε is a random error term.

4.3. Data Sources and Descriptive Statistics

The data of China's A-share listed manufacturing companies from 2011 to 2023 were selected as the research sample; the relevant data were primarily sourced from the Wind database and the CSMAR database. In addition, to ensure the accuracy and timeliness of the information, annual report data of the relevant companies were obtained from the official websites of the Shenzhen Stock Exchange and the Shanghai Stock Exchange. To reduce the impact of anomalous samples on the results of the study, ST companies and those that were demoted during the period were excluded, and samples with missing key indicators were excluded; the samples were subjected to 1 percent and 99 percent trimming. After a series of screenings, a total of 15,310 listed company sample data points meeting the research criteria were obtained.

5. Analysis of Empirical Results

5.1. Descriptive Statistics

Table 2 shows the results for descriptive statistics of the variables, including the mean, the standard deviation, the minimum value the maximum value, and the median value. The mean value of Dig is 1.266, the minimum value is 0, and the maximum value is 6.140. It indicates that the digitalization levels of manufacturing enterprises are significant differences. Meanwhile, the median of Dig is 1.099, which indicates that half of the firms in the sample hold relatively small digital transformation capabilities, and the digitization of firms has not been a uniform trend. The mean value of the TFP of manufacturing enterprises is 6.172, which is roughly comparable to the TFP of firms calculated in the previous works in the literature, and obviously less than the median (8.000). This value indicates that the overall distribution of enterprises' TFP is left-skewed.

Table 2. Descriptive statistics of variables.

Variable	Obs	Mean	SD	Min	Median	Max
TFP	15,310	6.172	0.797	3.000	8.000	10.000
Dig	15,310	1.266	1.290	0.000	1.099	6.140
Rd	15,310	18.07	1.505	7.170	18.050	25.030
Cost	15,310	0.092	0.176	0.003	0.0734	16.210
Age	15,310	10.46.	6.979	0.000	9.000	32.000
Size	15,310	22.15.	1.184	17.280	22.004	27.550
Leve	15,310	0.422	0.574	0.008	0.407	63.970
Roa	15,310	0.039	2.572	-76.760	0.067	282.000
Cash	15,310	0.049	0.072	-0.762	0.048	0.726
Board	15,310	8.452	1.615	0.000	9.000	18.000
Fist	15,310	33.220	14.340	2.380	30.920	100.000
Dual	15,310	0.322	0.467	0.000	0.000	1.000

5.2. Benchmark Regression Results

The results are summarized in Table 3, which presents the benchmark regression findings on the effect of digital technology on factor productivity in manufacturing. Column (1) presents the regression results with only the explanatory variables included. Column (2) further incorporates a series of control variables, such as firm age, firm size, asset/liability ratio, and return on assets. Column (3) controls for the firm, industry, province, and year fixed effects based on the aforementioned model. The regression results indicate that under different models, the regression coefficients of digital technology (Dig) are significantly positive at the 1% level, suggesting that digital technology has a significant promoting effect on the improvement of total factor productivity in the manufacturing industry. After fully considering other influencing factors and strictly incorporating the fixed effects, a 1% increase in the level of digital technology leads to a significant 2.3% improvement in the total factor productivity of the manufacturing industry. This conclusion not only reveals the tremendous potential of digital technology in enhancing manufacturing productivity but also provides strong empirical support for the resolution of the "Solow Paradox" in the digital age; thus, research hypothesis H1 proposed above is validated.

Table 3. Benchmark regression results.

	(1)	(2)	(3)
Dig	0.083 ***	0.037 ***	0.023 ***
	(16.830)	(9.835)	(3.291)
Age		0.005 ***	0.030

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		(6.450)	(1.251)
Size		0.427 ***	0.360 ***
		(92.045)	(21.175)
Leve		0.013	-0.006
		(1.550)	(-0.482)
Roa		0.002	-0.000
		(0.888)	(-0.129)
Cash		0.766 ***	0.837 ***
		(11.441)	(9.893)
Board		-0.005 *	0.007
		(-1.659)	(1.205)
Fist		0.003 ***	0.001
		(7.988)	(1.028)
Dual		-0.021 **	-0.018
		(-1.983)	(-1.119)
_cons	6.067 ***	-3.475 ***	-1.188 *
	(678.350)	(-36.214)	(-1.759)
Ind FE	NO	NO	YES
Pro FE	NO	NO	YES
Year FE	NO	NO	YES
N	15310	15310	15310
R^2	0.018	0.462	0.309

Note: *, **, *** represent the significant level of 10%, 5%, and 1%, respectively; the value in brackets below the coefficient is the robust standard-error t value.

5.3. Robustness Tests

5.3.1. Change the TFP Measurement method

The differences in the total factor productivity measurement methods of the manufacturing enterprises may affect the empirical results; in order to test the robustness of the results, this study address this issue by replacing the measurement methods used for the explanatory variables. The total factor productivity of the manufacturing industry is recalculated using four different methods: the semi-parametric method (LP), ordinary least squares (OLS), the fixed effects method (FE), and the generalized method of moments (GMM). The regression results presented in Column (1) to Column (4) of Table 4 demonstrate that regardless of the calculation method employed, the regression coefficients of the core explanatory variable, digital technology (Dig), are significantly positive, confirming that the conclusion that digital technology significantly enhances the total factor productivity of the manufacturing industry is robust.

Table 4. Robustness test results for change the TFP measurement method.

	(1)	(2)	(3)	(4)
Dig	0.029 ***	0.013 *	0.011 *	0.033 ***
	(4.145)	(1.862)	(1.591)	(4.486)
_cons	-3.395 ***	-5.226 ***	-6.120 ***	-0.872
	(-5.023)	(-8.460)	(-10.695)	(-1.425)
Controls	YES	YES	YES	YES
Ind FE	YES	YES	YES	YES

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Pro FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	15310	15310	15310	15310
R^2	0.380	0.546	0.581	0.211

Note: *, **, *** represent the significant level of 10%, 5%, and 1%, respectively; the value in brackets below the coefficient is the robust standard-error t value.

5.3.2. Substitution Core Explanatory Variable

The differences in the selection of digital technology indicators may affect the empirical results; this study attempts to address this issue by replacing the core explanatory variable. Considering that the productivity effects of digital technology may have a certain time lag, this study lags the core explanatory variable—digital technology—by one period and conducts the regression analysis again. The regression results are presented in Table 5, Column (1). Secondly, considering the differences in the length of digitally related text in annual reports, this study draws on the research method of Gu et al. (2023) [43] and uses the total frequency of the digitally related terms divided by the length of the digitally related segments in the annual reports (Dcg) as a proxy variable for the level of digital technology. The regression is re-estimated, and the results are presented in Table 5, Column (2). Thirdly, considering that the digital technology keyword information in the listed companies' annual reports only reflects anticipated tasks, this study draws on the research method of Manita et al., (2020) [44] and uses the proportion of intangible assets related to the digital economy at year end and the total intangible assets (Digi) as an alternative indicator of the digital technology level of the manufacturing enterprises. The regression analysis is re-conducted, and the results are presented in Table 5, Column (3). The above results show that the regression coefficient of Dig is positive at different significance levels, indicating that the productivity-enhancing effect of digital technology persists. This confirms that the baseline conclusions of this study are robust and reliable.

Table 5. Robustness test results for substitution Dig variable.

	(1)	(2)	(3)
L.Dig	0.029 ***		
	(3.870)		
Dcg		0.071 *	
		(1.927)	
Digi			2.144 **
			(1.980)
_cons	-2.759 ***	-1.258 *	-1.754 ***
	(-6.030)	(-1.826)	(-2.758)
Controls	YES	YES	YES
Ind FE	YES	YES	YES
Pro FE	YES	YES	YES
Year FE	YES	YES	YES
N	15310	15310	15310
R^2	0.300	0.313	0.301

Note: *, **, *** represent the significant level of 10%, 5%, and 1%, respectively; the value in brackets below the coefficient is the robust standard-error t value.

5.3.3. Adjustment of the Sample Size

Considering that specific types of samples may interfere with the estimation results, this study re-examines the baseline conclusions by excluding different types of samples. (1) Excluded research

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samples: Due to the high level of economic development in the municipalities (Beijing, Shanghai, Tianjin, and Chongqing), the firms located in the areas under the municipalities tend to have a higher level of digital technology, and the impact on their total factor productivity may be inconsistent with other industry samples. Thus, manufacturing enterprises located in municipalities are excluded from the re-estimation, and the regression results are shown in Column (1) of Table 6. (2) Reduced research time: In 2013, the State Council of China issued the "Broadband China" Strategy and Implementation Plan, promoting the development of digital infrastructure and supporting the digital transformation of enterprises. Therefore, this study excludes data from 2013 and earlier, re-estimating the sample for the period from 2014 to 2023. The regression results are presented in Table 6, Column (2). After adjusting the research sample, the regression coefficient of digital technology (Dig) remains significantly positive at the 1% level, indicating that the baseline regression conclusions are still robust.

Table 6. Robustness test results for adjustment the sample size and higher dimensional fixed effect.

	(1)	(2)	(3)
Dig	0.025***	0.024***	0.049***
	(3.298)	(2.973)	(5.635)
Cons	-0.963	-2.290***	-2.906***
	(-1.356)	(-5.058)	(-14.119)
Controls	YES	YES	YES
Ind FE	YES	YES	YES
Pro FE	YES	YES	YES
Year FE	YES	YES	YES
Ind-Year FE	NO	NO	YES
Pro-Year FE	NO	NO	YES
N	13005	12425	15222
R^2	0.314	0.258	0.550

Note: *, **, *** represent the significant level of 10%, 5%, and 1%, respectively; the value in brackets below the coefficient is the robust standard-error t value.

5.3.4. Higher Dimensional Fixed Effect

To rigorously control for potential omitted variables at the industry and regional levels and to avoid spurious associations between digital technology and total factor productivity, this study further adopts a high-dimensional fixed effects model for robustness testing. During the regression sample period, a series of industry- and provincial-level industrial policies were implemented, such as the "14th Five-Year Plan for Intelligent Manufacturing Development" and the "Digital Implementation Guidelines for Quality Management in Manufacturing (Trial)." These policies may influence the total factor productivity of enterprises by promoting industrial structure upgrading, enhancing investment and consumption attractiveness, optimizing resource allocation, fostering innovation-driven growth, and improving innovation capabilities. At the same time, industry and provincial characteristics, such as industry innovation capability, regional economic vitality, digital infrastructure development, and policy support intensity, may also impact the total factor productivity of enterprises. If these factors are not controlled for, it may be difficult to accurately identify the net effect of digital technology on the total factor productivity of the manufacturing industry. To address this, the study introduces province–year fixed effects and industry–year fixed effects in the regression analysis for re-estimation. The regression results are presented in Table 6, Column (3). The results show that the regression coefficient of digital technology (Dig) is significantly positive at the 1% level, confirming that the baseline conclusion of this study remains valid.

5.4. Endogeneity Tests

5.4.1. Instrumental Variable Method

When analyzing the impact of digital technology on the total factor productivity of the manufacturing industry, there may be endogeneity issues. On one hand, total factor productivity is influenced by a variety of complex factors, and some unobservable factors may play a role. On the other hand, total factor productivity is not only affected by the digital transformation of enterprises; the regional level of digital technology development also depends on factor inputs, which may lead to reverse causality. Therefore, this study employs the instrumental variable (IV) method to address potential issues of omitted variables and reverse causality, aiming to identify the net effect of digital technology on the total factor productivity (TFP) of the manufacturing industry. With reference to the research methods of Nunn & Qian (2014) [45] and Peng & Tao (2022) [46], this study selects the interaction term of urban terrain undulation and the time trend (IV1), as well as the interaction term of the spherical distance to Hangzhou and the time variable (IV2), as instrumental variables. The estimation results are presented in Table 7. The results in Columns (1) and (3) of Table 7 indicate that the regression coefficients of the selected instrumental variables are significantly positive at the 1% level, suggesting a positive correlation between the instrumental variables and the endogenous explanatory variables. The results in Columns (2) and (4) of Table 7 show that the regression coefficients of digital technology (Dig) are significantly positive at the 1% level, indicating that even after accounting for endogeneity, digital technology still enhances the total factor productivity (TFP) of the manufacturing industry. This confirms the robustness of the baseline conclusion in this study. In addition, the instrumental variables pass the relevance test.

Table 7. Robustness test results for instrumental variable method.

	(1) Dig	(2) TFP	(3) Dig	(4) TFP
Dig		0.017 *** (4.274)		0.026 *** (5.362)
IV1	0.118 *** (4.328)			
IV2			0.212 *** (3.212)	
Kleibergen-Paap rk LM	387.142		387.142	
Cragg–Donald Wald F	116.424		116.424	
Controls	YES	YES	YES	YES
Ind FE	YES	YES	YES	YES
Pro FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	15310	15310	15310	15310
R^2	0.198	0.201	0.332	0.422

Note: *, **, *** represent the significant level of 10%, 5%, and 1%, respectively; the value in brackets below the coefficient is the robust standard-error t value.

5.4.2. System GMM Method

To mitigate the endogeneity issues in the model estimation, this study uses the one-period lag of total factor productivity (TFP) as an instrumental variable and applies the system GMM estimation to address the endogeneity problem in dynamic panel data. The test results in Column (1) of Table 8 show that the p-value of the AR (1) test is significant at the 1% level, the p-value of the

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AR (2) test is greater than 0.1, and the p-value of the Hansen test is 0.147, which is also greater than 0.1. These results indicate that the chosen instrumental variable, the one-period lag of TFP, is appropriate. Column (1) presents the regression results, including the one-period lag of the dependent variable (L.TFP) and the core explanatory variable (Dig). The regression coefficient of L.TFP is 0.441 and is significant at the 1% level, indicating that a 1% increase in the previous period's total factor productivity (TFP) leads to a 0.441% increase in the current period's productivity. The regression coefficient of Dig is significantly positive at the 10% level, suggesting that digital technology enhances the total factor productivity of the manufacturing industry. These findings confirm the robustness of the study's conclusions.

Table 8. Robustness test results for system GMM method and multi-period DID method.

	System GMM method	Multi-period DID method
	(1)	(2)
Dig	0.023 *	
	(1.728)	
L.TFP	0.441 ***	
	(3.016)	
Treat×post		0.112 ***
		(4.415)
AR (1)	0	
AR (2)	0.171	
Hansen Test	0.147	
Controls	YES	YES
Ind FE	YES	YES
Pro FE	YES	YES
Year FE	YES	YES
N	12895	12476
R^2	0.619	0.754

Note: *, **, *** represent the significant level of 10%, 5%, and 1%, respectively; the value in brackets below the coefficient is the robust standard-error t value.

5.4.3. Multiperiod DID Method

This study further treats exogenous policy shocks as a quasi-natural experiment and constructs a difference-in-differences (DID) model with multiple periods to mitigate potential endogeneity issues. In August 2013, the State Council issued the "Broadband China" strategy and implementation plan, gradually advancing the construction of digital infrastructure. The Ministry of Industry and Information Technology (MIIT) and the National Development and Reform Commission (NDRC) selected a total of 120 cities as demonstration points in 2014, 2015, and 2016. Based on this, this study treats the "Broadband China" strategy as an exogenous policy shock and constructs a multiple-period difference-in-differences (DID) model. The model is as follows:

$$TFP_{it}=\beta_0+\beta_1 treat_{it}\times post_{it}+\beta_2 Controls+Ind_j+Pro_k+Year_t+\varepsilon_{it} \tag{4}$$

where is a dummy variable for the "Broadband China" strategy. The variable treat represents a dummy variable indicating whether the city where the enterprise is located has implemented the "Broadband China" strategy. If the strategy was implemented, the value is set to 1; otherwise, it is set to 0. Post is a dummy variable for the policy implementation year. If the city where the enterprise is located started the "Broadband China" strategy pilot in that year, the value is set to 1 for that year and the subsequent years; otherwise, it is set to 0. The settings for the other variables are consistent with those in the baseline regression. The results in Column (2) of Table 8 show that the regression coefficient of the "Broadband China" strategy policy is significantly positive at the 1%

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level, indicating that the "Broadband China" strategy policy contributes to the enhancement of the total factor productivity of the manufacturing industry, further supporting hypothesis H1.

6. Further Analysis

6.1. Mechanism Analysis

6.1.1. Enterprise Innovation Capacity

Columns (1) and (2) of Table 9 present the results of the analysis of the mechanism of corporate innovation capability. Column (1) reports the impact of digital technology on corporate innovation capability. The results show that the regression coefficient of digital technology (Dig) is significantly positive at the 1% level, indicating that digital technology promotes corporate innovation. Column (2) reports that the regression coefficient of corporate innovation capability (Rd) is significantly positive at the 1% level, and the regression coefficient of Dig is also significantly positive at the 1% level. This suggests that both corporate innovation capability and digital technology have a significant positive impact on corporate total factor productivity. This indicates that digital technology can enhance corporate innovation capability, thereby promoting the improvement of total factor productivity in the manufacturing industry. Thus, hypothesis H2 of this study is validated.

Table 9. Mechanism analysis result.

	(1) Rd	(2) TFP	(3) Cost	(4) TFP
Dig	0.071 ***	0.036 ***	-0.224 **	0.042 ***
	(6.204)	(4.836)	(-2.243)	(5.591)
Rd		0.087 ***		
		(8.025)		
Cost				-0.384 *
				(-1.750)
_cons	-2.985 ***	-0.977 **	0.664 ***	-0.978 **
	(-4.939)	(-2.101)	(5.365)	(-2.019)
Controls	YES	YES	YES	YES
Ind FE	YES	YES	YES	YES
Pro FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	15310	15310	15310	15310
R^2	0.585	0.412	0.435	0.412

Note: *, **, *** represent the significant level of 10%, 5%, and 1%, respectively; the value in brackets below the coefficient is the robust standard-error t value.

6.1.2. Operational Management Costs

Columns (3) and (4) of Table 9 present the results of the analysis of the operational management cost mechanism. Column (3) examines the impact of digital technology on corporate operational management costs. The results show that the regression coefficient of digital technology (Dig) is significantly negative at the 5% level, indicating that digital technology significantly reduces corporate operational management costs. Column (4) reports that the regression coefficient of operational management costs (Cost) is significantly negative at the 10% level, and the regression coefficient of Dig is significantly positive at the 1% level. This suggests that reducing corporate operational management costs and the development of digital technology can both promote the improvement of total factor productivity. This indicates that digital technology can promote the

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improvement of total factor productivity in the manufacturing industry by reducing operational management costs. Thus, hypothesis H3 of this study is validated.

6.2. Heterogeneity Analysis

6.2.1. Region Heterogeneity

To explore regional heterogeneity, this study classifies the provinces where the sample enterprises are located into eastern and central-western regions based on the macrogeographical environment. Columns (1) and (2) of Table 10 report the regression results of regional heterogeneity for enterprises in different regions. The results show that the regression coefficient of digital technology (Dig) in the eastern region is significantly positive at the 1% level, while the regression coefficient of Dig in the central and western regions is not significant. This indicates that digital technology has a significant positive impact on total factor productivity for enterprises in the eastern region, whereas its impact on total factor productivity for enterprises in the central and western regions is not significant. The reason is that the eastern region has greater advantages in terms of economy, technology, and infrastructure, which provide better conditions for digital transformation. The eastern region benefits from more abundant financial resources, technical talent, and market demand, along with a more mature environment for the application of digital technology, which can significantly enhance total factor productivity. In contrast, the central and western regions have relatively weaker infrastructure and digital resources, which constrain the efficiency-enhancing effects of digital technology on production.

Table 10. Heterogeneity analysis result.

	Eastern region (1)	Central-western region (2)	SOEs (3)	non-SOEs (4)	Large enterprises (5)	Small and medium sized enterprises (6)
Dig	0.065 *** (7.181)	-0.004 (-0.256)	0.094 *** (2.833)	0.038 *** (4.942)	0.045 ** (2.527)	0.055 *** (6.414)
_cons	-3.216 *** (-8.268)	-5.188 *** (-7.955)	-4.462 *** (-4.059)	-1.203 ** (-2.527)	-4.200*** (-6.757)	-3.414 *** (-7.890)
Controls	YES	YES	YES	YES	YES	YES
Ind FE	YES	YES	YES	YES	YES	YES
Pro FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
N	10859	4451	14119	1191	2890	12420
R^2	0.495	0.548	0.395	0.521	0.579	0.517

Note: *, **, *** represent the significant level of 10%, 5%, and 1%, respectively; the value in brackets below the coefficient is the robust standard-error t value.

6.2.2. Property Rights Heterogeneity

This study classifies the sample enterprises based on the nature of ownership into state-owned enterprises and non-state-owned enterprises. Columns (3) and (4) of Table 10 report the regression results of heterogeneity by ownership of the enterprise. The results show that the regression coefficients of digital technology (Dig) are significantly positive at the 1% level for both state-owned and non-state-owned enterprises, indicating that digital technology can enhance total factor productivity in the manufacturing industry. However, the regression coefficient of Dig is relatively larger for state-owned enterprises, suggesting that the improvement effect is significantly higher for state-owned enterprises compared to non-state-owned enterprises. The reason for this is that state-

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owned enterprises typically have more abundant resources and funding for digital transformation, along with stronger policy support and market advantages, enabling them to be more proactive and effective in technology adoption and application. In addition, state-owned enterprises have more standardized management systems and organizational structures, which facilitate the comprehensive implementation and integration of digital technology, further driving improvements in production efficiency.

6.2.3. Size Heterogeneity

This study classifies the sample enterprises into large enterprises and small and medium-sized enterprises (SMEs) based on the industry annual median of total assets. Columns (5) and (6) of Table 10 report the regression results of heterogeneity by enterprise size. The results show that the regression coefficients of digital technology (Dig) are significantly positive at the 5% level for large enterprises and at the 1% level for small and medium-sized enterprises, indicating that, regardless of enterprise size, digital technology can promote the improvement of total factor productivity in the manufacturing industry. The regression coefficient of Dig for small and medium-sized enterprises is larger than that for large enterprises, indicating that the effect of digital technology in promoting total factor productivity improvement is greater for small and medium-sized enterprises than for large enterprises. The underlying reason is that small and medium-sized enterprises typically respond more quickly in decision making and implementation, enabling them to rapidly adopt new technologies to enhance production efficiency. In addition, small and medium-sized enterprises place more emphasis on the application of digital technology in resource allocation to enhance their competitiveness, which results in more outstanding performance in technology application and innovation. In contrast, although large enterprises possess abundant resources, they may face organizational inertia and higher coordination costs, which can result in relatively lower effectiveness in the application of digital technology.

7. Conclusions

7.1. Main Conclusions and Insights

Digital technology is an important focus point for promoting the development of high-quality productivity, which is of great significance for the promotion of the high-quality development of China’s manufacturing industry. The main conclusions are as follows. First, digital technology significantly enhances total factor productivity in the manufacturing industry; this is a conclusion that still holds after the introduction of a variety of robustness tests and endogeneity tests, negating the productivity paradox of digitization. Second, digital technology promotes total factor productivity through the enhancement of enterprise innovation ability and the reduction in operation and management costs. Third, the productivity effect of digital technology is heterogeneous, and the promotion effect is more significant in eastern region enterprises, state-owned enterprises, and small and medium-sized enterprises.

Additionally, this study offers the following practical insights for promoting high quality development of manufacturing firms and the digital economy in the current era：

(1) Governments should increase policy support and encourage manufacturing enterprises to accelerate digital transformation through measures such as research and development subsidies and tax and fee reductions. Digital technology is crucial to promoting total factor productivity and the high-quality development of the manufacturing industry, and policy support can help enterprises reduce the costs and risks of digital transformation. At the same time, enterprises should also actively enhance the level of digital technology, transform the production process through automation and intelligent means, improve operational efficiency and innovation capacity, and ensure that technological inputs are effectively transformed into productivity to achieve sustainable development.

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(2) The promotion effect of digital technology on the total factor productivity of manufacturing enterprises is mainly realized through enterprise innovation and cost reduction; therefore, the government and enterprises should pay attention to innovation resource allocation. The government should establish an ideal innovation incentive mechanism to support enterprises' long-term investment in R&D and encourage small and medium-sized enterprises, especially those in the eastern region and state-owned enterprises, to increase their innovation efforts. In addition, the enterprises need to optimize their internal management mode, rationally allocate resources, promote the implementation of digital innovation projects, and closely integrate technological innovation with production efficiency to enhance their market competitiveness and innovation capacity.

(3) In response to the variability of digital technologies among different regions, ownership systems, and enterprise sizes, governments should guide the tilting of resources to narrow the regional and enterprise size gaps in the application of digital technologies. It is recommended that the sharing of resources between the eastern and the central and western regions be strengthened; furthermore, making the advanced technologies of eastern enterprises available to small and medium-sized enterprises and private enterprises should be promoted, so as to form a collaborative and win–win pattern of digital development. At the same time, the government can increase digitalization support for central and western China and small and medium-sized enterprises, enhance their ability to access resources in terms of infrastructure and technical talent, and promote industry-wide and region-wide digital transformation in the manufacturing industry.

7.2. Limitations and Future Prospects

While this study provides valuable insights, several limitations warrant attention. First, the measurement of digital technology adoption relies on aggregated enterprise-level data, potentially overlooking nuanced variations in specific technologies (e.g., AI vs. IoT) and their implementation depth. Second, the focus on China's manufacturing sector limits generalizability to other regions with distinct institutional or market conditions. Third, unobserved factors, such as managerial capabilities or supply chain dynamics, might mediate the relationship between digitalization and TFP but remain unaddressed. Lastly, integrating environmental metrics could assess how digital-driven productivity aligns with green manufacturing goals, addressing the dual challenges of efficiency and sustainability. Addressing these gaps would enrich the theoretical and practical understanding of digital transformation in global industrial ecosystems.

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