Open Journal of Business and Management, 2023, 11, 2525-2554
https://www.scirp.org/journal/ojbm
ISSN Online: 2329-3292
ISSN Print: 2329-3284

How Does Digital Technology Drive Total Factor Productivity in Enterprises? Empirical Evidence from Text Analysis

Shu Chen

School of Business Administration, Northeastern University, Shenyang, China
Email: chenshu0123@163.com

How to cite this paper: Chen, S. (2023). How Does Digital Technology Drive Total Factor Productivity in Enterprises? Empirical Evidence from Text Analysis. *Open Journal of Business and Management, 11,* 2525-2554.
https://doi.org/10.4236/ojbm.2023.115140

Received: July 28, 2023
Accepted: September 24, 2023
Published: September 27, 2023

Abstract

The deep integration of the digital economy with the real economy is a crucial pathway to achieving high-quality development in the new era. Based on the data of listed companies in China from 2012 to 2021, this paper uses the OLS regression model to empirically study how digital technology drives the total factor productivity of enterprises. The research results show that the enhancement of digital technology can significantly increase the total factor productivity of enterprises. At the same time, this paper selects enterprise innovation ability, cost and human capital structure as mediating variables to conduct mechanism tests to verify the specific path of digital technology affecting enterprise total factor productivity. Through group regression for heterogeneity research, this paper finds that the promotion effect of digital technology on enterprise total factor productivity is more obvious in non-high-tech industry enterprises and state-owned enterprises. Finally, this paper also conducts a robustness test by replacing the independent and dependent variables to prove the robustness of the above conclusions. This study provides micro evidence for the promotion effect of digital technology on enterprise efficiency, which is of great significance for enhancing total factor productivity and achieving high-quality economic development.

Keywords

Digital Technology, Digital Transformation, Total Factor Productivity, Text Analysis

1. Introduction

China's economy is currently facing an unprecedented "major transformation".

With the current economy entering a new phase of high-quality development, maintaining stable economic growth while improving quality and efficiency is a major challenge for China. Along with increasingly complex international conditions, prominent new and old contradictions, and numerous risks and challenges, finding solutions to promote China's economy to higher levels amidst crises and turning points is an urgent and crucial issue. The new wave of technological revolution stands as a key variable for China's economic breakthrough. Since the 21st century, the new technological revolution, centered around big data, the Internet of Things (IoT), artificial intelligence, and other technologies, has profoundly altered the operation and production modes of traditional industries, gradually becoming a critical factor reshaping global competitiveness and the global competitive landscape (Wang, 2020). Enterprises, as significant microeconomic entities in China's real economy, play a vital role in driving high-quality economic growth. The digital transformation of enterprises enables the deep integration of the Internet, IoT, big data, cloud computing, artificial intelligence, and their production and operational processes, thereby enhancing their total factor productivity and capacity to withstand external risks and impacts (Tian & Li, 2022).

Total factor productivity is an essential concept in macroeconomics and a critical tool for analyzing the sources of economic growth, particularly serving as a crucial basis for governments to formulate long-term sustainable growth policies (Guo & Jia, 2005). For enterprises, total factor productivity is an indicator of their overall production efficiency, considering various factors such as labor, capital, and technology. It helps enterprises assess operational performance, enhance competitiveness, promote innovation, and achieve sustainable development. While existing literature has extensively explored this topic, little attention has been given to the contribution of digital technology. In the context of an increasingly turbulent external environment, leveraging digital technology becomes pivotal for enterprises to improve their total factor productivity. Based on this premise, this study employs data from listed companies to investigate how digital technology drives total factor productivity in enterprises. The research findings demonstrate that digital technology is conducive to improving a firm's total factor productivity. Furthermore, the study reveals that enhanced innovation capabilities, reduced costs and expenses, and optimized human capital structure are important mechanisms through which digital technology drives total factor productivity. Heterogeneous analysis indicates that the promoting effect of digital transformation on total factor productivity is more pronounced in non-high-tech industries and state-owned enterprises.

The research in this paper makes significant contributions in the following aspects: First, we examined the positive impact of digitization on enterprise total factor productivity. The study empirically tests the favorable effect of digitization on total factor productivity in enterprises and explores the underlying mechanisms. It provides direct empirical evidence for the beneficial impact of digital transformation on a company's competitiveness. Second, we extended literature on the role of digital technology. Unlike previous studies, this research investigates the crucial role of digital technology from the perspective of total factor productivity, enriching the research landscape and providing a new angle of analysis. Third, our paper shows the micro-level evidence for the promotion of total factor productivity by digital technology. The study offers micro-level evidence for the facilitative role of digital technology in enhancing total factor productivity. It holds valuable policy implications for achieving higher total factor productivity in China's economic development. Finally, we incorporated the micro features and external environment in the analytical framework. By considering micro characteristics of enterprises and the external environment, this research helps companies develop digital transformation strategies tailored to their ownership nature and industry differences. Additionally, this analytical approach aids policymakers in formulating relevant policies and decisions to drive China's digital transformation process.

2. Literature Review

With the maturity and widespread adoption of the Internet and advanced communication technologies, digital transformation has gradually become a focal point for enterprises in terms of capital allocation, strategic planning, and investment decisions. Digital transformation is not simply an automation process; it involves a comprehensive restructuring of the organization and production methods within enterprises. By judiciously employing advanced digital technologies such as big data, IoT, and artificial intelligence, enterprises can reshape and enhance their production operations and service innovation (Ilvonen et al., 2018). As research on enterprise digital technology deepens, studies on its economic consequences have increased. In the realm of enterprise management, Yuan (2017) argues that digital transformation is a crucial means for companies to undergo transformation and upgrading, enabling them to change the way they create customer value through modern technology and innovative communication methods. Regarding corporate performance and innovation capabilities, Wu et al. (2021), based on data from Chinese listed companies between 2007 and 2018, empirically find that digital technology facilitates the improvement of research and development investment and innovation output performance, leading to enhanced corporate value and financial stability. Nwankpa & Roumani (2016), based on the resource-based view theory, also confirm the positive impact of digital technology on innovation and corporate performance.

Total factor productivity is influenced by various factors, and existing literature has extensively explored this topic from both macroeconomic and microeconomic perspectives, yielding rich research findings. At the macroeconomic level, factors such as marketization, reduced administrative intervention, judicial fairness, and efficiency significantly contribute to increased total factor productivity in enterprises (Wei et al., 2017). Additionally, macroeconomic factors such as the level of capital market development (Curtis, 2016), tax policies related to enterprise research and development (Minniti & Venturini, 2017), and industry environmental regulations (Shen et al., 2019) also impact enterprise total factor productivity. At the microeconomic level, scholars have primarily found that improving enterprise innovation capabilities (Chen & Sun, 2022), reducing the proportion of debt in capital structure (Dvoulety & Blaková, 2021), and enhancing the characteristics of equity incentive mechanisms (Wang, 2022) all contribute to higher total factor productivity in enterprises.

Regarding the impact of digital technology on total factor productivity, researchers have not yet reached a unanimous conclusion. Guo and Luo (2016) found that the Internet significantly promotes China's total factor productivity, which is driven by technological progress. Zeng et al. (2021) also study the positive impact of the level of enterprise digitization on total factor productivity, with a stronger effect observed in small and medium-sized enterprises. However, Acemoglu and Restrepo (2018), through research on the effects of automation and artificial intelligence on labor, wages, and employment demands, argue that excessive informatization can lead to resource waste and inefficient utilization of labor, thus indirectly inhibiting total factor productivity growth. Some scholars have also explored the mechanisms through which digital technology affects total factor productivity. Wen and Zhong (2022), through empirical research, find that digital infrastructure construction has a significant positive impact on enterprise total factor productivity. They further discover that promoting research and development innovation, reducing transaction costs, and improving management efficiency are the pathways through which the new digital infrastructure influences enterprise total factor productivity. Luo et al. (2023) find that digital technology innovation can promote total factor productivity through the improvement of innovation efficiency and resource allocation efficiency.

With the development of the digital economy, many scholars have researched the economic consequences of digital transformation. However, little attention has been given to the impact of digital technology on enterprise total factor productivity. Moreover, existing research on the factors influencing total factor productivity in enterprises has insufficiently explored the profound impact of digital transformation. Therefore, this study delves into the micro-level of enterprises, employing text mining methods to analyze word frequencies related to enterprise digital technology and digital transformation in annual reports. It constructs an enterprise digital transformation index to comprehensively understand the status of enterprise digital transformation. Subsequently, it conducts empirical analysis based on total factor productivity, revealing the significance of digital technology in enterprises. Furthermore, this research deeply investigates the mechanisms from the perspectives of innovation efficiency, enterprise costs, and human capital, providing valuable supplements to existing literature.

3. Theoretical Framework and Hypothesis

According to the theory of information asymmetry, in market economic activities, different individuals have varying levels of knowledge about relevant information, which affects transaction efficiency and fairness. Information asymmetry among market participants leads to increased transaction costs and decreased market liquidity, resulting in negative effects on firm performance and production efficiency. Digital transformation, as the process by which enterprises use digital technology and information means to change business models, enhance operational efficiency, and optimize customer experiences, helps to improve the phenomenon of information asymmetry within enterprises. Digital technology significantly enhances the availability of information for enterprises, enabling them to quickly understand market changes and trends through automated data collection, data-driven decision-making, and other methods. This empowers enterprises to make efficient and accurate business decisions, continually improving their operational management processes, and thereby achieving growth in total factor productivity (Li et al., 2022).

From the perspective of transaction cost theory, enterprises engage in internal and external trade-offs when conducting transactions, seeking the most economically efficient way to complete transactions while minimizing uncertainty and risk. Digital transformation can greatly reduce the transaction costs for enterprises, maximizing the efficiency of financial resource utilization. Advancements in digital technology not only accelerate the transmission, processing, and delivery of information, thereby reducing the cost of information collection for enterprises (Malone et al., 1987), but also help enterprises track and communicate with partners in real-time to ensure smooth transactions and minimize risks and losses caused by counterparty defaults (Clemons et al., 1993). Additionally, digital transformation contributes to lower financing costs, enhances risk control capabilities in the capital allocation process, and ultimately positively impacts a firm's total factor productivity (Tan et al., 2022). Based on the above analysis, this study proposes Hypothesis 1:

Hypothesis 1 (H1): Digital technology drives improvements in enterprise total factor productivity.

Digital technology can impact enterprise total factor productivity through various channels. Digital transformation helps enterprises optimize business processes and reduce operational costs (Li et al., 2018), accelerate innovation and improve economic performance (Chen, 2019). Additionally, increasing innovation capabilities, tax reductions, and optimizing resource allocation are all ways to enhance enterprise total factor productivity (Tian & Lu, 2021; Hsueh & Klenow, 2009). Therefore, this paper will discuss the mechanisms through which digital technology affects enterprise total factor productivity in the following three aspects.

Based on endogenous growth theory, through technological progress and innovation, enterprises can improve production efficiency and achieve sustained growth in total factor productivity. Existing research also supports this theory. Ai & Peng (2021), based on the perspective of absorptive capacity, find that independent research and development, technology introduction, and other methods promote the development of enterprise total factor productivity. Liu et al. (2022) empirically demonstrate that technological innovation capabilities have a significant positive impact on enterprise total factor productivity. Moreover, digital transformation introduces digital technology into enterprises, changing business models, processes, and value chains, which is an essential way to enhance innovation capabilities. An increasing number of enterprises view data as a crucial driving factor for innovation and productivity enhancement, as data elements accelerate internal information communication and knowledge spillover (Tan et al., 2015). Digital technology provides an efficient collaborative innovation foundation for enterprises' research and development efforts, ensuring high-quality innovation (Tang et al., 2022).

Digital transformation involves converting traditional business processes and operations into digital form, using information technology and digital tools to improve business processes and achieve higher total factor productivity by lowering costs. On the one hand, enterprise digital transformation utilizes the Internet information network and fully leverages integrated digital platforms, integrating internal data resources, significantly improving overall operational efficiency, achieving data connectivity along the upstream and downstream industrial chains, and reducing transaction costs for enterprises (Wang & Zhang, 2023). On the other hand, digital technology can alleviate the problem of information asymmetry within enterprises, helping them quickly understand market trends and changes, and reducing the cost of extensive information collection. Liu et al. (2023) empirically demonstrate that digital technology significantly improves information symmetry and reduces operating costs. Furthermore, digital technology aids in reducing capital costs and increasing enterprise value (Min et al., 2023).

By optimizing the human capital structure, digital technology can enhance enterprise total factor productivity. Digital technology helps enterprises better utilize human resources, increase work efficiency and quality, and enhance decision-making capabilities, thereby strengthening the competitiveness and sustainable development capacity of enterprises. Firstly, digital transformation, with advanced digital technology and information systems, achieves the transformation and upgrading of enterprise processes by replacing low-skilled labor demands with computer programs that perform routine or repetitive basic tasks (Yami et al., 2021), optimizing the enterprise's human capital structure. Secondly, digital technology has a skill-biased feature, significantly increasing fixed asset and research and development investments in enterprises, leading to increased demand for high-skilled labor, which helps in the transformation and upgrading of enterprise labor structure (Ye et al., 2022). This transformation also expands the scale of enterprise operations, further improving total factor productivity efficiency.

Based on the above analysis, the following hypotheses are proposed:

Hypothesis 2a (H2a): Digital technology enhances enterprise total factor productivity by improving innovation capabilities.

Hypothesis 2b (H2b): Digital technology enhances enterprise total factor productivity by reducing costs.

Hypothesis 2c (H2c): Digital technology enhances enterprise total factor productivity by optimizing the human capital structure.

4. Empirical Design

4.1. Data Source

This study selects all A-share listed companies in China from 2012 to 2021 as the research sample, and conducts the following sample screening: 1) Exclude companies with unavailable MD&A paragraphs, resulting in 9561 observations removed; 2) Exclude ST-listed companies and financial industry companies, resulting in 2378 observations removed; 3) Exclude listed companies with missing total factor productivity indicators, resulting in 4058 observations removed; 4) Exclude observations with missing important control variables, resulting in 1877 observations removed. The final sample consists of 3727 companies with a total of 24,865 company-year observations. The research data primarily come from the CSMAR and WIND databases.

4.2. Variable Definitions

Total Factor Productivity (TFP)

For the measurement of total factor productivity, the Solow residual method, based on the Cobb-Douglas production function, was originally proposed by Solow in 1957. This method calculates the "residual" output growth rate after deducting the input growth rates of various factors, but it relies on strict assumptions and is mainly used for macro-level measurement. As data availability improved, scholars proposed more methods for calculating total factor productivity at the firm level. Among them, the Levinsohn and Petrin (LP) method (Levinsohn & Petrin, 2003) and the Olley and Pakes (OP) method (Olley & Pakes, 1996) have been widely applied in related research to overcome endogeneity issues in OLS and fixed-effect methods. Therefore, in this study, the LP method and the OP method are used to estimate firm-level total factor productivity, and robustness checks are conducted using the generalized method of moments (GMM) (2009) to verify the results.

Corporate Digital Technology (DT)

Following the research by Wu et al. (2021), Yuan et al. (2021), Zhao et al. (2021), and Wu et al. (2022), a Python-based web scraping program is used to collect and organize the management's discussion and analysis (MD & A) section of all A-share listed companies' annual reports. The program extracts all text content and matches all keywords related to corporate digital transformation and digital technology applications, and then calculates the frequency of appearance of these digital technology keywords (DT) as a measure of the extent of digital technology application in each company. Additionally, for robustness checks, a custom dictionary established by Wu et al. (2021) and Yuan et al. (2021) is used to count the frequency of digital technology keywords.

Control Variables

This study controls for the following variables: First, the firm's own operating conditions are important factors affecting total factor productivity, so the study includes control variables such as firm size (*Size*), leverage ratio (*LEV*), profitability (*ROA*), fixed asset ratio (*Fix*), inventory level (*Stock*), cash holdings (*Cash*), free cash flow ratio (*FC*), and firm age (*Age*). Second, corporate governance structure and internal control conditions are also crucial factors influencing firms' decisions on digital transformation. Therefore, the study controls for variables related to ownership structure (*SOE*), ownership balance (*Balance*), CEO dual role (*Dual*), management ownership percentage (*MgtHolding*), board size (*Board*), proportion of independent directors (Ind Director), and whether the firm has one of the "Big Four" audit firms (*Four*). Additionally, the study controls for year-specific time factors (*Time*) and firm-specific characteristics (*Firm*).

4.3. Model

In order to study the impact of digital technology on *TFP*, the OLS regression model (1) is developed with reference to the study by Zhao et al. (2021). The dependent variable denotes the proxy indicator for enterprise total factor productivity of *i* enterprise in *t* year. The key independent variable represented the degree of enterprise digital technology application of *i* enterprise in *t* year. The crucial coefficient in the model is denoted as, representing the regression coefficient of digital technology (*DT*) on enterprise total factor productivity (*TFP*). The sign and magnitude of this coefficient indicate the extent of the impact of digital technology on enterprise total factor productivity.

Furthermore, the model includes an intercept term denoted as, a set of control variables represented by, which are used to control for other factors that might influence total factor productivity. The set of control variables is denoted as. At the same time, in order to account for the individual time-invariant characteristics of enterprises affecting total factor productivity, the model also includes enterprise-specific fixed effects as. Additionally, to control for time-related variations in total factor productivity across the entire sample, the model includes time fixed effects denoted as. Finally, the model incorporates a random disturbance term, which captures other unexplained random factors that may influence total factor productivity. The main variables and definitions are as shown in **Table 1**.

5. Empirical Analysis Results

5.1. Descriptive Statistics

The descriptive statistics are presented in **Table 2** for the main variables. The

Table 1. Main variables and definitions.

	Variable Name	Symbol	Variable Definition
Dependent Variable	Total Factor Productivity	*TFP*	The OP and LP methods are employed for computing the dependent variable, which represents the total factor productivity of the companies The GMM method is used for robustness testing (Lu & Lian, 2012; Yang, 2015).
Independent Variable	Digital Technology	*DT*	To measure the extent of enterprise digital technology adoption, we refer to the works of Wu et al. (2021), Yuan et al. (2021), Zhao et al. (2021), and Wu et al. (2022). Python programming language is utilized to develop web-crawling programs for collecting and organizing textual content from the management discussion and analysis section of annual reports of all A-share listed companies. Relevant keywords related to enterprise digital technology are matched and the total frequency of their occurrence (*DT*) is calculated.
		DT_F	A custom digital dictionary established by Wu et al. (2021) is solely used to calculate the frequency of occurrence of digital technology keywords.
		DT_X	A custom digital dictionary established by Yuan et al. (2021) is solely used to calculate the frequency of occurrence of digital technology keywords.
		DT_Z	A custom digital dictionary established by Zhao et al. (2021) is solely used to calculate the frequency of occurrence of digital technology keywords.
		DT_W	A custom digital dictionary established by Wu et al. (2021) is solely used to calculate the frequency of occurrence of digital technology keywords.
		DT_FX	A custom digital dictionaries developed by Yuan et al. (2021), Zhao et al. (2021), and Wu et al. (2022) are separately used to calculate the frequency of occurrence of digital technology keywords.
Control variables	Company Size	*Size*	The natural logarithm of total assets.
	Debt-to-Asset Ratio	*LEV*	The ratio of total liabilities to total assets.
	Profitability	*ROA*	The return on assets.
	Fixed Asset Ratio	*Fix*	The ratio of fixed assets to total assets.
	Inventory Level	*Stock*	The ratio of inventory to total assets.
	Cash Holdings	*Cash*	The ratio of initial cash and cash equivalents to total assets.
	Free Cash Flow Ratio	*FC*	The ratio of enterprise free cash flow to total assets.
	Company Age	*Age*	The age of the company at the time of listing.
	Ownership Property	*SOE*	A dummy variable is used to indicate state-owned enterprises (1) and non-state-owned enterprises (0).
	Equity Balance	*Balance*	The difference between the maximum and minimum shareholding percentages of the largest shareholder is divided by the sum of these percentages to compute the governance balance variable.
	Dual Chairman and CEO	*Dual*	A dummy variable is used to indicate companies where the chairman also holds the position of general manager (1) and companies where they are separate (0).

Continued

	Management Shareholding Proportion	*MgtHolding*	The proportion of management's shareholding relative to all shareholders is calculated.
	Board Size	*Board*	The number of directors on the board.
	Proportion of Independent Directors	*Inddirector*	The proportion of independent directors relative to all board members.
	Audited by the "Big Four" Accounting Firms	*Four*	A dummy variable is used to indicate companies audited by the "Big Four" accounting firms (1) and others (0).
	Time Fixed Effects	*Time*	Year-specific dummy variables.
	Individual Fixed Effects	*Firm*	Individual firm-specific dummy variables.

Table 2. Descriptive statistics of main variables.

Variable	*Mean*	*Med*	*S. D.*	*Min*	*Max*	*N*
DT	0.324	0.126	0.546	0	7.630	24,865
DT_F	0.0584	0.00691	0.142	0	2.306	24,865
DT_X	0.0349	0	0.0917	0	1.814	24,865
DT_Z	0.156	0.0759	0.227	0	2.935	24,865
DT_W	0.0742	0.0207	0.150	0	2.279	24,865
TFP-LP	8.370	8.279	1.071	3.908	13.18	24,865
TFP-OP	6.688	6.587	0.901	2.458	11.43	24,865
TFP-GMM	3.809	3.703	0.876	-0.352	9.586	24,865
Size	22.20	22.03	1.299	16.12	28.55	24,865
LEV	0.436	0.416	0.522	0.00797	63.97	24,865
ROA	0.0292	0.0356	0.397	-48.32	8.441	24,865
Fix	0.211	0.181	0.157	9.00e-06	0.929	24,865
Stock	0.286	0.223	0.267	0	4.299	24,865
Cash	0.151	0.113	0.126	6.58e-05	1.563	24,865
FC	0.000460	0.0174	0.348	-46.24	4.449	24,865
Age	18.17	18	5.637	2	63	24,865
SOE	0.335	0	0.472	0	1	24,865
Balance	0.737	0.578	0.607	0.00310	4	24,865
Dual	0.287	0	0.452	0	1	24,865
Mgt Holding	13.75	0.866	19.58	0	99.45	24,865
Board	8.487	9	1.648	3	18	24,865
Ind director	37.62	36.36	5.534	14.29	80	24,865
Four	0.0498	0	0.218	0	1	24,865

5.2. Baseline Regression

Table 3 presents the results of the baseline regression. Columns (1) and (3) show the regression results with only the core explanatory variable, which is the level of digital technology adoption. When the dependent variable is calculated using the OP method and the LP method, respectively, the regression coefficients are both significantly positive at the 1% level, indicating that digital technology contributes to improving enterprise total factor productivity (*TFP*). Columns (2) and (4) display the results after incorporating control variables. After considering the impact of the control variables, the regression coefficients of digital technology show a slight reduction, but the positive correlation between the level of digital technology adoption and enterprise TFP remains significant, thus validating hypothesis 1. Examining the regression results of the control variables, the coefficients of firm size, leverage ratio, return on assets, fixed asset ratio, inventory level, and firm age are all significantly positive at the 1% level, suggesting that a certain level of leverage, improved profitability and sales capability, and overall expansion of firm size contribute to higher total factor productivity and enable enterprises to achieve high-quality development.

Table 3. The impact of digital technology on enterprise total factor productivity.

	(1)	(2)	(3)	(4)
	TFP-OP		*TFP-LP*	
DT	0.0876***	0.0195**	0.1264***	0.0339***
	(9.6665)	(2.4814)	(12.6095)	(4.2835)
Size		0.4104***		0.5690***
		(70.3928)		(96.9921)
LEV		0.0492***		0.0554***
		(4.3850)		(4.9005)
ROA		0.0558***		0.0678***
		(4.3870)		(5.2962)
Fix		−1.0883***		−1.3171***
		(−33.1839)		(−39.9131)
Stock		0.1891***		0.2701***
		(9.9090)		(14.0657)
Cash		0.0360		0.0469*
		(1.3409)		(1.7348)
FC		−0.0104		−0.0350***
		(−1.1018)		(−3.6988)
Age		0.0193***		0.0065***
		(14.1743)		(4.7228)

Continued

SOE		−0.0839***		−0.0626***
		(−4.8978)		(−3.6356)
Balance		−0.0018		−0.0122
		(−0.2244)		(−1.5146)
Dual		−0.0223***		−0.0202**
		(−2.8099)		(−2.5335)
Mgt Holding		−0.0002		−0.0001
		(−0.4949)		(−0.1675)
Board		0.0052		0.0101***
		(1.6021)		(3.1315)
Ind Director		0.0011		0.0012
		(1.3590)		(1.4815)
Four		−0.0056		0.0141
		(−0.2318)		(0.5769)
Constant	6.3469***	−2.6424***	7.9897***	−4.2780***
	(714.4182)	(−20.3379)	(813.6129)	(−32.7232)
Year FE	N	Y	N	Y
Firm FE	N	Y	N	Y
Observations	24865	24865	24865	24865
Adjusted R^2	0.0774	0.3127	0.0748	0.4289

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The numbers in parentheses represent the t-statistics. This table presents the results of the analysis for Hypothesis 1. The sample includes 24,865 firm-year observations from the CSMAR and WIND databases, with all variables winsorized at the 1% level. The baseline regression model is used, controlling for year and firm fixed effects. In **Table 3**, columns (1) and (2) show the dependent variable as total factor productivity (TFP) calculated using the Olley and Pakes (OP) method, while columns (3) and (4) show TFP calculated using the Levinsohn and Petrin (LP) method. The independent variable in all columns is the frequency of digital technology keywords (DT). Columns (1) and (3) do not control for other variables, while columns (2) and (4) control for the other variables.

mean of the dependent variable, enterprise total factor productivity (*TFP*), is 6.688% (OP method) and 8.370% (LP method), with standard deviations of 0.901% (OP method) and 1.071% (LP method). The minimum values are 2.458% (OP method) and 3.908% (LP method), while the maximum values are 11.43% (OP method) and 13.18% (LP method), indicating significant variation in TFP among companies. The mean of the keyword frequency DT, representing the degree of enterprise digital technology application, is 32.4%, with a standard deviation of 54.6%, indicating substantial differences in digitalization levels among companies. Furthermore, the values of DT obtained using different scholars' dictionaries as reference also show notable discrepancies. For instance, using the dictionary by Zhao et al. (2021) (*DT_Z*) results in a digitalization keyword frequency of 15.6%, while the dictionary by Yuan et al. (2021) (*DT_X*) yields only 3.49% of total keywords as digital technology related. The average age of listed companies in the sample is 18.17 years, and there is relatively little variation in the total asset size. Overall, the financial performance and scale distribution of the sample companies appear reasonable. The average debt-to-asset ratio (*LEV*) of the sample companies is 43.6%, with a standard deviation of 52.2%, indicating significant variations in their debt situations. Regarding corporate governance, approximately 28.7% of the sample companies have a dual chairman and CEO role (*Dual*), the average board size (*Board*) is around 8.487, and the management holding ratio (*Mgtholding*) is approximately 13.75%. The majority of the companies in the sample are non-state-owned enterprises ($SOE = 0$).

5.3. Mechanism Testing

In this section, we analyze the specific mechanisms through which digital technology promotes firm's total factor productivity (*TFP*). To test the mechanism of firm's innovation capability, as technological innovation is largely achieved through research and development (*R & D*) investment, innovation activities, and knowledge accumulation, this study employs R & D investment as the mediating variable. To examine the mechanism of firm's costs, we measure it using the cost-to-revenue ratio (*Cost*), calculated as follows: (operating costs + administrative expenses)/operating revenue. For testing the mechanism of human capital structure, the proportion of employees with a bachelor's degree or higher (*Degree*) is used as the mediating variable. The complete mediation model (2) is presented as follows, with INTER representing the mediating variable.

Table 4 presents the results of the mechanism testing using R & D investment as the mediating variable. Columns (2) and (5) show that with an increase in R & D investment, firm's total factor productivity (TFP) significantly rises. This is because the increase in R & D investment enhances firm's innovation capability, leading to process simplification, technological improvements, and process optimization, which greatly improves the firm's production efficiency. Column (6) reports the results of the mechanism test for the LP method, showing that the estimated coefficient of R & D investment is significantly positive at the 1% level, and the variable representing the level of digital technology application is significantly positive at the 10% level. This indicates that digital technology application drives the growth of firm's total factor productivity by increasing R & D investment and enhancing the firm's innovation capability, thereby verifying hypothesis 2a.

In **Table 5**, columns (2) and (5) show that a significant reduction in operating costs can promote an increase in firm's total factor productivity (*TFP*). Columns (3) and (6) present the results of the mechanism test for cost reduction. It can be

Table 4. The results of the mechanism test for firm's innovation capability.

	(1)	(2)	(3)	(4)	(5)	(6)
		TFP-OP			*TFP-LP*	
DT	0.0195**		0.0012	0.0339***		0.0124*
	(2.4814)		(0.1789)	(4.2835)		(1.7746)
R & D		0.0558***	0.0558***		0.0809***	0.0808***
		(16.4610)	(16.4493)		(23.7274)	(23.6705)
Size	0.4104***	0.3690***	0.3689***	0.5690***	0.5057***	0.5049***
	(70.3928)	(56.3531)	(56.1946)	(96.9921)	(76.7610)	(76.4422)
LEV	0.0492***	0.0733***	0.0733***	0.0554***	0.0982***	0.0987***
	(4.3850)	(5.2827)	(5.2850)	(4.9005)	(7.0336)	(7.0668)
ROA	0.0558***	0.0976***	0.0977***	0.0678***	0.1297***	0.1301***
	(4.3870)	(6.6257)	(6.6275)	(5.2962)	(8.7481)	(8.7747)
Fix	−1.0883***	−1.1110***	−1.1109***	−1.3171***	−1.4069***	−1.4052***
	(−33.1839)	(−33.2729)	(−33.2526)	(−39.9131)	(−41.8738)	(−41.8068)
Stock	0.1891***	0.2800***	0.2800***	0.2701***	0.4226***	0.4228***
	(9.9090)	(12.5500)	(12.5504)	(14.0657)	(18.8264)	(18.8352)
Cash	0.0360	−0.0237	−0.0236	0.0469*	−0.0163	−0.0148
	(1.3409)	(−0.9343)	(−0.9280)	(1.7348)	(−0.6386)	(−0.5810)
FC	−0.0104	−0.0234**	−0.0233**	−0.0350***	−0.0427***	−0.0425***
	(−1.1018)	(−2.4576)	(−2.4549)	(−3.6988)	(−4.4630)	(−4.4397)
Age	0.0193***	0.0189***	0.0188***	0.0065***	0.0046***	0.0043***
	(14.1743)	(14.2230)	(14.1150)	(4.7228)	(3.4417)	(3.2239)
SOE	−0.0839***	−0.0681***	−0.0681***	−0.0626***	−0.0377**	−0.0375**
	(−4.8978)	(−4.1193)	(−4.1176)	(−3.6356)	(−2.2662)	(−2.2525)
Balance	−0.0018	0.0003	0.0003	−0.0122	−0.0033	−0.0032
	(−0.2244)	(0.0436)	(0.0447)	(−1.5146)	(−0.4344)	(−0.4235)
Dual	−0.0223***	−0.0181**	−0.0181**	−0.0202**	−0.0171**	−0.0172**
	(−2.8099)	(−2.4699)	(−2.4700)	(−2.5335)	(−2.3212)	(−2.3234)
Mgt Holding	−0.0002	−0.0002	−0.0002	−0.0001	−0.0003	−0.0003
	(−0.4949)	(−0.6084)	(−0.6102)	(−0.1675)	(−0.8811)	(−0.8990)
Board	0.0052	0.0096***	0.0096***	0.0101***	0.0108***	0.0107***
	(1.6021)	(3.1924)	(3.1909)	(3.1315)	(3.5725)	(3.5593)
Ind Director	0.0011	0.0006	0.0006	0.0012	0.0004	0.0004
	(1.3590)	(0.8589)	(0.8601)	(1.4815)	(0.5876)	(0.6001)

Continued

Four	−0.0056	0.0232	0.0232	0.0141	0.0423*	0.0424*
	(−0.2318)	(0.9967)	(0.9972)	(0.5769)	(1.8098)	(1.8151)
Constant	−2.6424***	−2.7700***	−2.7678***	−4.2780***	−4.2920***	−4.2709***
	(−20.3379)	(−21.1423)	(−21.0395)	(−32.7232)	(−32.5569)	(−32.2663)
Year FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Observations	24865	21469	21469	24865	21469	21469
Adjusted R^2	0.3127	0.3978	0.3978	0.4289	0.5112	0.5112

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The numbers in parentheses represent the t-statistics. This table provides the analysis results for hypothesis 2a. The mechanism test for firm's innovation capability was conducted using the intermediate effect model, controlling for firm and year fixed effects. In this table, columns (1), (2), and (3) present the results with total factor productivity (TFP) calculated using the OP method, while columns (4), (5), and (6) present the results with TFP calculated using the LP method. The independent variable is the frequency of digital technology (DT). Columns (1) and (4) report the regression results for digital technology, columns (2) and (5) report the regression results for R & D investment, and columns (3) and (6) explain the extent to which digital technology affects TFP through the pathway of R & D investment.

Table 5. The results of the mechanism test for firm costs.

	(1)	(2)	(3)	(4)	(5)	(6)
		TFP-OP			*TFP-LP*	
DT	0.0195**		0.0185**	0.0339***		0.0328***
	(2.4814)		(2.3797)	(4.2835)		(4.2057)
Cost		−0.2481***	−0.2480***		−0.2633***	−0.2631***
		(−24.2166)	(−24.2056)		(−25.5731)	(−25.5592)
Size	0.4104***	0.3963***	0.3951***	0.5690***	0.5548***	0.5528***
	(70.3928)	(68.7186)	(68.3021)	(96.9921)	(95.7371)	(95.1113)
LEV	0.0492***	0.0630***	0.0634***	0.0554***	0.0697***	0.0704***
	(4.3850)	(5.6815)	(5.7149)	(4.9005)	(6.2550)	(6.3157)
ROA	0.0558***	0.0720***	0.0723***	0.0678***	0.0847***	0.0853***
	(4.3870)	(5.7285)	(5.7535)	(5.2962)	(6.7096)	(6.7555)
Fix	−1.0883***	−1.0844***	−1.0813***	−1.3171***	−1.3153***	−1.3096***
	(−33.1839)	(−33.5439)	(−33.4208)	(−39.9131)	(−40.4849)	(−40.2928)
Stock	0.1891***	0.1842***	0.1845***	0.2701***	0.2646***	0.2652***
	(9.9090)	(9.7812)	(9.8003)	(14.0657)	(13.9850)	(14.0223)
Cash	0.0360	0.0346	0.0367	0.0469*	0.0439*	0.0476*
	(1.3409)	(1.3076)	(1.3872)	(1.7348)	(1.6494)	(1.7909)

Continued

FC	−0.0104	0.0006	0.0008	−0.0350***	−0.0234**	−0.0232**
	(−1.1018)	(0.0690)	(0.0862)	(−3.6988)	(−2.5113)	(−2.4818)
Age	0.0193***	0.0209***	0.0205***	0.0065***	0.0084***	0.0077***
	(14.1743)	(15.6512)	(15.2540)	(4.7228)	(6.2844)	(5.7364)
SOE	−0.0839***	−0.0756***	−0.0752***	−0.0626***	−0.0541***	−0.0534***
	(−4.8978)	(−4.4731)	(−4.4510)	(−3.6356)	(−3.1872)	(−3.1488)
Balance	−0.0018	−0.0034	−0.0033	−0.0122	−0.0140*	−0.0138*
	(−0.2244)	(−0.4255)	(−0.4156)	(−1.5146)	(−1.7534)	(−1.7364)
Dual	−0.0223***	−0.0227***	−0.0227***	−0.0202**	−0.0208***	−0.0206***
	(−2.8099)	(−2.9039)	(−2.8953)	(−2.5335)	(−2.6364)	(−2.6218)
Mgt Holding	−0.0002	−0.0005	−0.0005	−0.0001	−0.0004	−0.0004
	(−0.4949)	(−1.4778)	(−1.4886)	(−0.1675)	(−1.1933)	(−1.2125)
Board	0.0052	0.0040	0.0039	0.0101***	0.0090***	0.0088***
	(1.6021)	(1.2671)	(1.2374)	(3.1315)	(2.8226)	(2.7709)
Ind Director	0.0011	0.0010	0.0010	0.0012	0.0011	0.0011
	(1.3590)	(1.2497)	(1.2545)	(1.4815)	(1.3653)	(1.3742)
Four	−0.0056	−0.0051	−0.0050	0.0141	0.0146	0.0149
	(−0.2318)	(−0.2125)	(−0.2064)	(0.5769)	(0.6049)	(0.6159)
Constant	−2.6424***	−2.1401***	−2.1149***	−4.2780***	−3.7632***	−3.7183***
	(−20.3379)	(−16.5155)	(−16.2679)	(−32.7232)	(−28.8981)	(−28.4697)
Year FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Observations	24865	24865	24865	24865	24865	24865
Adjusted R^2	0.3127	0.3311	0.3312	0.4289	0.4456	0.4460

Note: *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively. The numbers in parentheses are t-statistics. This table presents the analysis results for hypothesis 2b. The intermediary effect model is used to test the mechanism of firm costs, controlling for fixed effects of year and firm. In this table, columns (1), (2), and (3) represent the dependent variable of total factor productivity (TFP) calculated using the OP method, while columns (4), (5), and (6) represent the TFP calculated using the LP method. The independent variable in all columns is the frequency of digital technology (DT). Columns (1) and (4) report the regression results of digital technology, columns (2) and (5) report the regression results of firm costs, and columns (3) and (6) explain the impact of digital technology on TFP through the pathway of firm costs.

observed that digital technology significantly increases TFP by reducing costs, confirming hypothesis 2b in this study. This is because digital transformation enables firms to integrate resources and achieve cost-effectiveness through digital technologies. Additionally, it helps alleviate information asymmetry between supply and demand, leading to reduced operating costs and enhanced firm's total factor productivity.

Table 6 presents the estimation results in columns (2) and (5), indicating that an increase in the proportion of highly educated employees, i.e., optimization of firm's human capital structure, significantly promotes the rise in total factor productivity (*TFP*). Column (6) reports the intermediary mechanism test results for the impact of human capital structure on TFP using the LP method. The estimated coefficient of human capital structure is significantly positive at the 1% level, and the variable of digital technology application is also significantly positive at the 1% level, confirming hypothesis 2c. Digital transformation enables the replacement of some low-skilled labor and enhances the demand for high-skilled talents, leading to adaptive changes in the firm's human capital structure and further driving the improvement in production efficiency.

Table 6. The results of the mechanism test for the firm's human capital structure.

	(1)	(2)	(3)	(4)	(5)	(6)
		TFP-OP			*TFP-LP*	
DT	0.0195**		0.0045	0.0339***		0.0209***
	(2.4814)		(0.5780)	(4.2835)		(2.6510)
Degree		0.0050***	0.0050***		0.0019***	0.0019***
		(17.3035)	(17.2817)		(6.4027)	(6.3308)
Size	0.4104***	0.3902***	0.3899***	0.5690***	0.5542***	0.5530***
	(70.3928)	(67.8598)	(67.6327)	(96.9921)	(95.1286)	(94.6903)
LEV	0.0492***	0.1376***	0.1376***	0.0554***	0.1581***	0.1582***
	(4.3850)	(10.0825)	(10.0833)	(4.9005)	(11.4353)	(11.4416)
ROA	0.0558***	0.1322***	0.1322***	0.0678***	0.1459***	0.1460***
	(4.3870)	(9.8121)	(9.8132)	(5.2962)	(10.6875)	(10.6951)
Fix	−1.0883***	−0.9487***	−0.9482***	−1.3171***	−1.2440***	−1.2414***
	(−33.1839)	(−29.3027)	(−29.2715)	(−39.9131)	(−37.9256)	(−37.8341)
Stock	0.1891***	0.2033***	0.2034***	0.2701***	0.2631***	0.2635***
	(9.9090)	(10.8409)	(10.8446)	(14.0657)	(13.8468)	(13.8680)
Cash	0.0360	0.0219	0.0224	0.0469*	0.0398	0.0422
	(1.3409)	(0.8249)	(0.8439)	(1.7348)	(1.4818)	(1.5708)
FC	−0.0104	0.0400***	0.0400***	−0.0350***	0.0041	0.0042
	(−1.1018)	(3.3428)	(3.3437)	(−3.6988)	(0.3386)	(0.3430)
Age	0.0193***	0.0165***	0.0164***	0.0065***	0.0068***	0.0064***
	(14.1743)	(12.3368)	(12.1837)	(4.7228)	(5.0122)	(4.6676)

Continued

SOE	−0.0839***	−0.0883***	−0.0882***	−0.0626***	−0.0677***	−0.0672***
	(−4.8978)	(−5.3421)	(−5.3340)	(−3.6356)	(−4.0461)	(−4.0119)
Balance	−0.0018	0.0045	0.0045	−0.0122	−0.0029	−0.0027
	(−0.2244)	(0.5754)	(0.5799)	(−1.5146)	(−0.3660)	(−0.3452)
Dual	−0.0223***	−0.0247***	−0.0247***	−0.0202**	−0.0248***	−0.0247***
	(−2.8099)	(−3.2012)	(−3.1999)	(−2.5335)	(−3.1676)	(−3.1623)
Mgt Holding	−0.0002	−0.0005	−0.0005	−0.0001	−0.0003	−0.0003
	(−0.4949)	(−1.4721)	(−1.4726)	(−0.1675)	(−1.0730)	(−1.0753)
Board	0.0052	0.0056*	0.0056*	0.0101***	0.0104***	0.0102***
	(1.6021)	(1.8019)	(1.7896)	(3.1315)	(3.2967)	(3.2421)
Ind Director	0.0011	0.0012	0.0012	0.0012	0.0013*	0.0013*
	(1.3590)	(1.6428)	(1.6421)	(1.4815)	(1.7056)	(1.7025)
Four	−0.0056	−0.0069	−0.0069	0.0141	0.0129	0.0131
	(−0.2318)	(−0.2978)	(−0.2961)	(0.5769)	(0.5463)	(0.5539)
Constant	−2.6424***	−2.3474***	−2.3415***	−4.2780***	−4.0540***	−4.0269***
	(−20.3379)	(−18.4468)	(−18.3430)	(−32.7232)	(−31.4459)	(−31.1423)
Year FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Observations	24865	24209	24209	24865	24209	24209
Adjusted R^2	0.3127	0.3355	0.3354	0.4289	0.4433	0.4434

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The numbers in parentheses represent t-statistics. This table provides the analysis results for hypothesis 2c. The intermediary mechanism test for the impact of firm's human capital structure on total factor productivity (TFP) is conducted, controlling for fixed effects of year and firm individual effects. In this analysis, columns (1), (2), and (3) present the dependent variable as TFP calculated using the OP method, while columns (4), (5), and (6) use the LP method. The independent variable in all columns is the frequency of digital technology (DT). Columns (1) and (4) report the regression results for digital technology, columns (2) and (5) report the regression results for human capital, and columns (3) and (6) explain the impact of digital technology on TFP through the pathway of human capital.

5.4. Heterogeneity Analysis

Regression by Industry Attribute

In this section, we conduct a heterogeneity analysis by grouping the results based on industry attributes. On one hand, high-tech enterprises typically possess higher capabilities and proficiency in technology, innovation, and management, resulting in relatively higher initial levels of digitalization and production efficiency. For highly efficient companies[1], digital transformation may only bring limited improvements. However, for non-high-tech enterprises, the incremental effect of applying digital technology in digital transformation can be more significant, leading to a more positive impact on total factor productivity. On the other hand, high-tech enterprises often rely on advanced technology and complex business processes, which may require more resources and time for digital transformation. In contrast, non-high-tech enterprises may have relatively simpler business processes, leading to higher implementation efficiency in digital transformation.

The regression results of the heterogeneity analysis are presented in **Table 7**. Columns (1) and (3) show the results for high-tech industry enterprises, while the remaining two columns present the results for non-high-tech industry enterprises. The regression results indicate that the impact of digital technology on total factor productivity is not significant for high-tech industry enterprises. However, for non-high-tech industry enterprises, the effect of digital technology on total factor productivity exhibits significant positive correlation at a 5% level, indicating a more pronounced role of digital technology in non-high-tech industries and validating the findings of this study.

Regression by Property Rights Attributes

The ownership attribute has a significant impact on the decisions and endowments related to enterprise digital transformation. Firstly, state-owned enterprises (*SOEs*) possess certain resource advantages. Achieving digital transformation requires extensive utilization of digital technology, substantial investment in intelligent manufacturing, and the establishment of modern information systems. SOEs typically have more resources, including funds, human resources, and technological patents. This inherent resource endowment enables SOEs to engage in more research and development (*R & D*) and innovation activities (Li & Song, 2010), which drive innovation and technological upgrading, thereby enhancing total factor productivity. Secondly, SOEs enjoy policy advantages. They play a crucial role and act as pillars in the national economy, often receiving government support in the form of financial subsidies, tax incentives, and policy guidance. Therefore, SOEs with strong national credibility are more likely to receive additional attention during the process of digital transformation, which helps them secure dominant positions in the market and form effective feedback loops to enhance total factor productivity (Qi et al., 2021). Lastly, SOEs

[1]In order to investigate whether the impact of digital technology on firm's total factor productivity (TFP) is influenced by industry-specific differences, this study classified high-tech listed companies based on the "Catalogue for Guiding Industry Restructuring (Strategic Emerging Industries)" and the "Catalogue for Guiding Industry Restructuring (2012 Trial Version)". According to the "Guidelines for Industry Classification of Listed Companies (Revised in 2012)", industry codes were assigned to high-tech listed companies. The high-tech industry codes include three categories and nineteen major categories: Manufacturing (C), Information Transmission, Software, and Information Technology Services (1), and Scientific Research and Technology Services (M). The nineteen major categories include C25, C26, C27, C28, C29, C31, C32, C34, C35, C36, C37, C38, C39, C40, C41, I63, I64, I65, and M73. A virtual industry attribute variable "Tech" was created, assuming a value of 1 if the company belongs to the high-tech industry and 0 otherwise.

Table 7. Heterogeneity analysis of high-tech and non-high-tech industry enterprises.

	(1)	(2)	(3)	(4)
	TFP-OP		*TFP-LP*	
	high-tech	non-high-tech	high-tech	non-high-tech
DT	−0.0006	0.1035**	0.0120	0.1187**
	(−0.0784)	(4.6273)	(1.5512)	(5.3373)
Size	0.3599**	0.4675**	0.5227**	0.6209**
	(52.0763)	(46.6480)	(74.1967)	(62.3418)
LEV	0.0093	0.0510**	0.0415**	0.0446**
	(0.5429)	(3.0938)	(2.3897)	(2.7255)
ROA	0.3445**	0.0235	0.3690**	0.0199
	(13.6420)	(1.3045)	(14.3329)	(1.1118)
Fix	−1.1882**	−0.9353**	−1.4374**	−1.1514**
	(−30.5491)	(−16.7356)	(−36.2536)	(−20.7303)
Stock	0.2941**	0.1215**	0.4207**	0.1796**
	(10.2084)	(4.4457)	(14.3249)	(6.6106)
Cash	−0.0765**	0.2150**	−0.0614**	0.2479**
	(−2.5856)	(4.1689)	(−2.0347)	(4.8373)
FC	0.0577**	0.0157	0.0226	−0.0059
	(4.2703)	(1.0384)	(1.6401)	(−0.3948)
Age	0.0302**	0.0060**	0.0174**	−0.0070**
	(18.9852)	(2.5244)	(10.7542)	(−2.9786)
SOE	−0.0631**	−0.1254**	−0.0429**	−0.1018**
	(−3.2624)	(−4.0517)	(−2.1755)	(−3.3108)
Balance	0.0005	0.0050	−0.0069	−0.0085
	(0.0535)	(0.3424)	(−0.7460)	(−0.5938)
Dual	−0.0233**	−0.0245*	−0.0137	−0.0350**
	(−2.6268)	(−1.6826)	(−1.5214)	(−2.4188)
Mgt Holding	−0.0003	0.0000	−0.0002	0.0004
	(−0.7774)	(0.0169)	(−0.5351)	(0.6737)
Board	0.0090**	−0.0006	0.0115**	0.0080
	(2.4294)	(−0.1040)	(3.0290)	(1.4307)
Ind Director	−0.0002	0.0024*	−0.0002	0.0028**
	(−0.2177)	(1.7792)	(−0.2340)	(2.0474)
Four	0.0187	−0.0349	0.0449	−0.0193
	(0.6491)	(−0.8444)	(1.5330)	(−0.4693)

Continued

Constant	−1.7222**	−3.6647**	−3.4275**	−5.2458**
	(−11.2460)	(−16.2996)	(−21.9553)	(−23.4774)
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Observations	14884	9981	14884	9981
Adjusted R^2	0.3844	0.2663	0.4924	0.3837

Note: *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. The numbers in parentheses are t-statistics. This table presents the results of grouping the sample companies based on industry attributes and conducting regression with fixed effects controlling for annual and firm-specific fixed effects. In columns (1) and (2), the dependent variable is total factor productivity calculated using the OP method, while in columns (3) and (4), the dependent variable is total factor productivity calculated using the LP method. The independent variable in all columns is the frequency of digital technology keywords (DT). Additionally, columns (1) and (3) represent the results for high-tech industry enterprises, while columns (2) and (4) represent the results for non-high-tech industry enterprises.

possess organizational advantages. They usually have more stable and standardized organizational structures and management practices, along with stronger organizational and execution capabilities. This enables SOEs to better drive the implementation of digital technology projects and ensure the effective implementation of various measures, thereby improving total factor productivity.

To examine the impact of ownership attribute on the relationship between digital technology and total factor productivity, this study conducted grouped regression based on the ownership attribute (*SOEs*) for the sample companies. Table 8 presents the results of the heterogeneity test, confirming the conclusion of this study that there are significant differences in the impact of digital technology on total factor productivity between SOEs and non-SOEs, with a relatively greater enhancement effect on total factor productivity observed in SOEs.

5.5. Robustness Tests

Replacement of Independent Variable

To ensure the robustness of the conclusions, this study first examines the reliability of the model by using alternative measures for the explanatory variable. The original digital transformation index system constructed in the previous sections was modified based on the more frequently cited digital technology and digitization indicators proposed by Wu et al. (2021) and Yuan et al. (2021). A new digital technology lexicon was established using these indicators. The regression results are shown in Table 9, indicating that the impact of digital technology on firm's total factor productivity (*TFP*) is significantly positive at the 5% level. Furthermore, when using only the lexicon built based on the most

Table 8. Heterogeneity test between state-owned enterprises (*SOEs*) and non-state-owned enterprises.

	(1)	(2)	(3)	(4)
	TFP-OP		*TFP-LP*	
	SOE	Non SOE	SOE	Non SOE
DT	0.0381**	0.0089	0.0541**	0.0231**
	−2.3749	−0.9893	−3.3988	−2.5123
Size	0.3831**	0.4091**	0.5360**	0.5655**
	−36.9225	−56.0058	−52.0329	−76.1978
LEV	0.0624*	0.0227*	0.1341**	0.0229*
	−1.774	−1.8296	−3.8427	−1.8191
ROA	0.2258**	0.0169	0.2219**	0.0207
	−8.0048	−1.0941	−7.9237	−1.3182
Fix	−0.8250**	−1.2455**	−1.1209**	−1.4560**
	(−15.9605)	(−29.3897)	(−21.8405)	(−33.8193)
Stock	0.1619**	0.1975**	0.1684**	0.3169**
	−5.2553	−8.1109	−5.5067	−12.807
Cash	0.2373**	0.0119	0.2303**	0.0379
	−4.2161	−0.3826	−4.1205	−1.1998
FC	0.0633**	−0.0112	0.0142	−0.0300**
	−3.5317	(−0.9133)	−0.7961	(−2.4105)
Age	0.0146**	0.0257**	−0.0003	0.0146**
	−7.0586	−13.859	(−0.1273)	−7.7358
Balance	0.0282*	−0.008	0.016	−0.0154
	−1.7998	(−0.8263)	−1.0288	(−1.5683)
Dual	0.0077	−0.0285**	−0.0039	−0.0232**
	−0.5005	(−3.0664)	(−0.2584)	(−2.4520)
Mgt Holding	−0.0005	0.0004	−0.0023	0.0007*
	(−0.1816)	−1.1928	(−0.8325)	−1.8407
Board	0.0068	0.0081*	0.0124**	0.0118**
	−1.4576	−1.853	−2.6652	−2.6581
Ind Director	0.0007	0.0025**	0.0013	0.0023**
	−0.5954	−2.376	−1.1432	−2.2144
Four	−0.017	0.0225	−0.0204	0.0652*
	(−0.4924)	−0.6621	(−0.5929)	−1.8935
Constant	−2.0286**	−2.8170**	−3.4929**	−4.4328**
	(−8.8885)	(−17.4327)	(−15.4145)	(−27.0031)

Continued

Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Observations	8339	16526	8339	16526
Adjusted R^2	0.261	0.3306	0.3746	0.444

Note: *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. The numbers in parentheses are t-statistics. This table presents grouped regression results based on property rights attributes of the sampled companies, controlling for annual and firm-specific fixed effects. In columns (1) and (2), the dependent variable is the total factor productivity (*TFP*) calculated using the OP method, while in columns (3) and (4), the dependent variable is TFP calculated using the LP method. The independent variable in all columns is the frequency of digital technology keywords (*DT*). Additionally, columns (1) and (3) represent results for state-owned enterprises (*SOEs*), while columns (2) and (4) represent results for non-state-owned enterprises.

Table 9. Robustness test with replacement of independent variable.

	(1) *TFP-OP*	(2) *TFP-LP*	(3) *TFP-OP*	(4) *TFP-LP*
DT_FX	0.0402**	0.0644**		
	(2.0130)	(3.2081)		
DT_F			0.0473*	0.0697**
			(1.6990)	(2.4889)
Size	0.4107**	0.5697**	0.4109**	0.5701**
	(70.5107)	(97.1812)	(70.5758)	(97.2858)
LEV	0.0491**	0.0550**	0.0490**	0.0550**
	(4.3691)	(4.8697)	(4.3675)	(4.8645)
ROA	0.0556**	0.0675**	0.0556**	0.0674**
	(4.3746)	(5.2722)	(4.3735)	(5.2684)
Fix	−1.0891**	−1.3189**	−1.0894**	−1.3197**
	(−33.2109)	(−39.9633)	(−33.2163)	(−39.9793)
Stock	0.1886**	0.2692**	0.1889**	0.2698**
	(9.8818)	(14.0179)	(9.8995)	(14.0439)
Cash	0.0356	0.0460*	0.0358	0.0460*
	(1.3276)	(1.7023)	(1.3335)	(1.7019)
FC	−0.0104	−0.0352**	−0.0105	−0.0352**
	(−1.1110)	(−3.7154)	(−1.1119)	(−3.7176)
Age	0.0195**	0.0068**	0.0196**	0.0071**
	(14.3769)	(5.0096)	(14.5085)	(5.1838)
SOE	−0.0844**	−0.0635**	−0.0841**	−0.0630**
	(−4.9267)	(−3.6844)	(−4.9093)	(−3.6581)

Continued

Balance	−0.0018	−0.0123	−0.0020	−0.0125
	(−0.2301)	(−1.5248)	(−0.2442)	(−1.5459)
Dual	−0.0222**	−0.0201**	−0.0221**	−0.0200**
	(−2.8006)	(−2.5197)	(−2.7883)	(−2.5041)
Mgt Holding	−0.0002	−0.0000	−0.0002	−0.0001
	(−0.4781)	(−0.1393)	(−0.4922)	(−0.1605)
Board	0.0052	0.0102**	0.0052	0.0102**
	(1.6121)	(3.1511)	(1.6036)	(3.1411)
Ind Director	0.0011	0.0012	0.0010	0.0011
	(1.3643)	(1.4892)	(1.3489)	(1.4653)
Four	−0.0054	0.0144	−0.0054	0.0144
	(−0.2237)	(0.5888)	(−0.2234)	(0.5873)
Constant	−2.6510**	−4.2953**	−2.6561**	−4.3052**
	(−20.4237)	(−32.8832)	(−20.4759)	(−32.9775)
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Observations	24865	24865	24865	24865
Adjusted R^2	0.3127	0.4287	0.3126	0.4286

Note: *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. The numbers in parentheses indicate the t-statistics. This table presents the results of a robustness test conducted by replacing the independent variable metrics to ensure the reliability of the conclusions. The analysis controls for fixed effects of year and company. In columns (1) and (3), the dependent variable is the total factor productivity (TFP) calculated using the OP method, while in columns (2) and (4), it is calculated using the LP method. The independent variable in columns (1) and (2) is the frequency of digital technology terms based on the digital dictionary proposed by (Wu et al., 2021) and (Yuan et al., 2021), while in columns (3) and (4), it is solely based on the digital dictionary established by (Wu et al., 2021).

cited study by Wu et al. (2021), the results remain robust, showing a significant positive effect of digital technology on firm's total factor productivity, even with a narrower range of digital transformation lexicon compared to the original study.

Replacement of Dependent Variable

Following the approach of (Luo et al., 2023) and (Lao & Mo, 2018), this study replaced the dependent variable with the total factor productivity (*TFP*) of enterprises estimated using the GMM method. The regression results are presented in **Table 10**, which show that the impact of digital technology on the mechanism of enterprise TFP remains consistent with the previous conclusions. This further confirms that digital technology significantly promotes the improvement of

Table 10. Robustness test with replacement of dependent variable.

	(1)	(2)	(3)	(4)	(5)
			TFP-GMM		
DT					0.0283***
					(3.27)
DT_W				0.0509*	
				(1.73)	
DT_Z			0.0766***		
			(3.78)		
DT_X		0.107**			
		(2.31)			
DT_F	0.0769**				
	(2.51)				
Size	0.167***	0.167***	0.166***	0.167***	0.166***
	(26.07)	(26.13)	(25.93)	(26.09)	(25.93)
LEV	0.0449***	0.0447***	0.0453***	0.0449***	0.0452***
	(3.63)	(3.62)	(3.66)	(3.63)	(3.65)
ROA	0.0615***	0.0613***	0.0617***	0.0615***	0.0617***
	(4.39)	(4.38)	(4.41)	(4.39)	(4.40)
Fix	−2.620***	−2.622***	−2.617***	−2.623***	−2.619***
	(−72.56)	(−72.66)	(−72.48)	(−72.67)	(−72.53)
Stock	0.216***	0.215***	0.217***	0.216***	0.216***
	(10.26)	(10.21)	(10.31)	(10.26)	(10.28)
Cash	0.0306	0.0276	0.0302	0.0288	0.0305
	(1.04)	(0.94)	(1.02)	(0.97)	(1.03)
FC	−0.0244**	−0.0245**	−0.0243**	−0.0244**	−0.0243**
	(−2.36)	(−2.37)	(−2.35)	(−2.36)	(−2.35)
Age	0.0174***	0.0171***	0.0168***	0.0171***	0.0169***
	(11.65)	(11.42)	(11.22)	(11.41)	(11.27)
SOE	−0.0753***	−0.0763***	−0.0739***	−0.0756***	−0.0750***
	(−3.99)	(−4.05)	(−3.92)	(−4.01)	(−3.98)
Balance	0.00269	0.00308	0.00297	0.00287	0.00293
	(0.30)	(0.35)	(0.34)	(0.32)	(0.33)
Dual	−0.0240***	−0.0246***	−0.0245***	−0.0244***	−0.0243***
	(−2.75)	(−2.81)	(−2.80)	(−2.79)	(−2.78)

Continued

Mgt Holding	2.24e−05	3.81e−05	8.24e−06	2.77e−05	2.16e−05
	(0.06)	(0.11)	(0.02)	(0.08)	(0.06)
Board	0.00319	0.00338	0.00311	0.00333	0.00320
	(0.90)	(0.95)	(0.88)	(0.94)	(0.90)
Ind Director	0.000888	0.000925	0.000881	0.000903	0.000900
	(1.04)	(1.08)	(1.03)	(1.06)	(1.05)
Four	0.00324	0.00278	0.00319	0.00227	0.00288
	(0.12)	(0.10)	(0.12)	(0.08)	(0.11)
Constant	0.245*	0.242*	0.265*	0.243*	0.262*
	(1.71)	(1.70)	(1.85)	(1.70)	(1.83)
Year FE	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y
Observations	24,865	24,865	24,865	24,865	24,865
Adjusted R^2	0.200	0.200	0.200	0.200	0.200

Note: *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. The numbers in parentheses are t-statistics. This table conducts robustness tests by replacing the dependent variable and controlling for fixed effects at the year and company levels. The dependent variable in all columns is the total factor productivity (TFP) calculated using the GMM method. The independent variables in columns (1) to (4) are the word frequencies of digital technology from separate dictionaries established by Wu et al. (2021), Yuan et al. (2021), Zhao et al. (2021), and Wu et al. (2022), respectively. Column (5) represents the word frequency of digital technology from the combined collection of all dictionaries.

enterprise total factor productivity. Even after replacing the dependent variable, hypothesis 1 of the study still holds.

6. Conclusion

This study is based on data from listed companies in China and investigates whether digital technology can enhance a firm's total factor productivity (*TFP*). The results demonstrate that the application of digital technology significantly improves a firm's TFP. Further analysis reveals that the enhancement of firm innovation capability, cost reduction, and optimization of human capital structure are important mechanisms through which digital technology elevates TFP. The heterogeneity analysis shows that the positive impact of digital technology on TFP is more pronounced in non-high-tech industries and state-owned enterprises. The robustness tests confirm the robustness of the findings.

The implications for corporate management are twofold. Firstly, management should give strategic attention to TFP indicators and promote the shift towards environmentally friendly and sustainable growth models. By continuously innovating and improving resource utilization efficiency, firms can enhance their competitiveness in the industry. Secondly, active digital transformation is necessary to empower operations and management with modern digital technology. This will enable firms to adapt more effectively to the ever-changing business environment and lay a solid microeconomic foundation for China's economic development. It is crucial for companies to formulate appropriate digital transformation strategies based on their actual development situation. State-owned enterprises and non-high-tech firms should focus on digital technology development strategies, leveraging digital advantages in existing markets and technologies to revitalize traditional resources and capabilities, thus boosting TFP. Non-state-owned enterprises should adopt a long-term digital transformation strategy, enhancing their digital infrastructure to address resource limitations.

The study offers insights to policymakers. The comprehensive promotion of China's economic transformation towards digitalization, intelligence, consumption, and services is a wise move to empower the real economy and achieve high-quality economic development. The government should actively construct and improve policies and support systems to facilitate enterprise digital transformation from a strategic standpoint. Specifically, the government should strengthen digital infrastructure construction by accelerating network development, establishing digital infrastructure platforms, and enhancing cybersecurity to provide better hardware support for enterprises. Additionally, continuous improvement of digital policies and regulations is crucial, with a particular focus on providing policy incentives and technical support to non-state-owned enterprises that lack relevant technologies and resources. For instance, reducing taxes and fees related to digital transformation can encourage enterprises to actively participate in this process. Moreover, strengthening intellectual property protection and providing a conducive research and development environment can encourage enterprises to enhance technological innovation and embrace digital transformation.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

References

Acemoglu, D. M., & Restrepo, P. M. (2018). Artificial Intelligence, Automation, and Work. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3098384

Ai, Y., & Peng, D. (2021). Independent Innovation, Opening Up, and Total Factor Productivity of High-Tech Industries: A Study Based on the Perspective of Absorptive Capacity. *Finance and Economics, 9,* 68-75.

Chen, C. (2019). Research on the Construction of the Capability System of Traditional Enterprise Digital Transformation. *People's Forum: Academic Frontiers, No. 18,* 6-12. https://doi.org/10.16619/j.cnki.rmltxsqy.2019.18.001

Chen, S., & Sun, G. (2022). Directors' Appointments in Related Industries, Innovation Capability, and Total Factor Productivity of Enterprises. *Economic and Management*

Research, 43, 37-58. https://doi.org/10.13502/j.cnki.issn1000-7636.2022.07.003

Clemons, E. K., Reddi, S. P., & Row, M. C. (1993). The Impact of Information Technology on the Organization of Economic Activity: The "Move to the Middle" Hypothesis. *Journal of Management Information Systems, 10,* 9-35. https://doi.org/10.1080/07421222.1993.11517998

Curtis, C. C. (2016). Economic Reforms and the Evolution of China's Total Factor Productivity. *Review of Economic Dynamics, 21,* 225-245. https://doi.org/10.1016/j.red.2015.02.005

Dvoulety, O., & Blaková, I. (2021). Exploring Firm-Level and Sectoral Variation in Total Factor Productivity (TFP). *International Journal of Entrepreneurial Behaviour & Research, 6,* 1526-1547. https://doi.org/10.1108/IJEBR-11-2020-0744

Guo, J., & Luo, P. (2016). Does the Internet Promote China's Total Factor Productivity? *Management World, No. 10,* 34-49. https://doi.org/10.19744/j.cnki.11-1235/f.2016.10.003

Guo, Q., & Jia, J. (2005). Estimation of China's Total Factor Productivity: 1979-2004. *Economic Research, No. 6,* 51-60. https://www.cnki.com.cn/Article/CJFDTOTAL-JJYJ200506004.htm

Hsueh, C. T., & Klenow, P. J. (2009). Misallocation and Manufacturing TFP in China and India. *The Quarterly Journal of Economics, 124,* 1403-1448. https://doi.org/10.1162/qjec.2009.124.4.1403

Ilvonen, I., Thalmann, S., Manhart, M., & Sillaber, C. (2018). Reconciling Digital Transformation and Knowledge Protection: A Research Agenda. *Knowledge Management Research & Practice, 16,* 235-244. https://doi.org/10.1080/14778238.2018.1445427

Lao, G., & Mo, B. (2018). Study on the Efficiency and Total Factor Productivity of China's Securities Companies—Based on Hicks-Moorsteen TFP Index Method. *Technology and Investment, 9,* 52-67. https://doi.org/10.4236/ti.2018.91004

Levinsohn, J., & Petrin, A. (2003). Estimating Production Functions Using Inputs to Control for Unobservables. *The Review of Economic Studies, 70,* 317-341. https://doi.org/10.1111/1467-937X.00246

Li, C., & Song, M. (2010). Innovation Activities of Chinese Manufacturing Enterprises: The Role of Ownership and CEO Incentives. *Economic Research, 45,* 55-67. http://qikan.cqvip.com/Qikan/Article/Detail?id=33922191

Li, L., Su, F., Zhang, W. et al. (2018). Digital Transformation by SME Entrepreneurs: A Capability Perspective. *Information Systems Journal, 28,* 1129-1157. https://doi.org/10.1111/isj.12153

Li, Y., Xiang, Z., & Liao, C. (2022). Research on the Configuration Path of Advanced Manufacturing Digital Transformation: Based on the Theoretical Framework of "Technology-Organization-Environment". *Science and Technology Management Research, 42,* 119-126. https://www.cnki.com.cn/Article/CJFDTOTAL-KJGL202203015.htm

Liu, J., Zhou, K., Zhang, Y., & Tang, F. (2023). The Effect of Financial Digital Transformation on Financial Performance: The Intermediary Effect of Information Symmetry and Operating Costs. *Sustainability, 15,* Article 5059. https://doi.org/10.3390/su15065059

Liu, K., Liu, R., Li, T. et al. (2022). Manufacturing Service Level, Technological Innovation, and Total Factor Productivity. *Theoretical Research in Finance and Economics, No. 2,* 89-101. https://doi.org/10.13894/j.cnki.jfet.2022.02.005

Lu, X., & Lian, Y. (2012). Estimation of China's Industrial Enterprise Total Factor Productivity: 1999-2007. *Economic Research, 11,* 541-558. https://doi.org/10.13821/j.cnki.ceq.2012.02.013

Luo, J., Zhang, J., & Li, K. (2023). How Does Digital Technology Innovation Drive the Total Factor Productivity of Manufacturing Enterprises? Evidence from Patent Data of Listed Companies. *Journal of Finance and Economics Research, 49,* 95-109. https://doi.org/10.16538/j.cnki.jfe.20221118.101

Malone, T. W., Yates, J., & Benjamin, R. I. (1987). Electronic Markets and Electronic Hierarchies. *Communication of the ACM, 30,* 484-497. https://doi.org/10.1145/214762.214766

Min, H., Huang, J., Zhang, K. et al. (2023). Does Digital Transformation of Enterprises Help Reduce the Cost of Equity Capital. *Mathematical Biosciences and Engineering, 20,* 6498-6516. https://doi.org/10.3934/mbe.2023280

Minniti, A., & Venturini, F. (2017). R&D Policy, Productivity Growth, and Distance to Frontier. *Economics Letters, 159,* 92-94. https://doi.org/10.1016/j.econlet.2017.04.005

Nwankpa, J. K., & Roumani, Y. (2016). IT Capability and Digital Transformation: A Firm Performance Perspective. In *International Conference on Information Systems*. https://www.researchgate.net/publication/362751432_IT_Capability_and_Digital_Transformation_A_Firm_Performance_Perspective_Completed_Research_Paper

Olley, G. S., & Pakes, A. (1996). The Dynamics of Productivity in the Telecommunications Equipment Industry. *Econometrica, 64,* 1263-1297. https://doi.org/10.2307/2171831

Qi, Y., Du, B., & Wen, X. (2021). Digital Transformation in State-Owned Enterprises: Mission Integration and Model Selection—A Case Study of Digital Transformation Practices in Three Central Enterprises. *Management World, 37,* 137-158+10. https://doi.org/10.19744/j.cnki.11-1235/f.2021.0176

Shen, N., Liao, H., & Deng, R. (2019). Different Types of Environmental Regulations and the Heterogeneous Influence on the Environmental Total Factor Productivity: Empirical Analysis of China's Industry. *Journal of Cleaner Production, 211,* 171-184. https://doi.org/10.1016/j.jclepro.2018.11.170

Tan, K. H., Zhan, Y. Z., Ji, G. et al. (2015). Harvesting Big Data to Enhance Supply Chain Innovation Capabilities: An Analytic Infrastructure Based on Deduction Graph. *International Journal of Production Economics, 165,* 223-233. https://doi.org/10.1016/j.ijpe.2014.12.034

Tan, Z., Zhao, X., Pan, J., & Tan, J. (2022). The Value of Digital Transformation: From the Perspective of Enterprise Cash Holdings. *Financial Research, 48,* 64-78. https://doi.org/10.16538/j.cnki.jfe.20220113.103

Tang, S., Su, X., & Zhao, D. (2022). Financial Technology and Enterprise Digital Transformation: Based on the Perspective of Enterprise Lifecycle. *Finance & Economics, 2,* 17-32.

Tian, L., & Lu, X. (2021). Tax Reduction, Enterprise Entry and Exit, and Total Factor Productivity. *Management World, 37,* 56-77. https://doi.org/10.19744/j.cnki.11-1235/f.20211123.001

Tian, X., & Li, R. (2022). Empowering Real Economy Transformation and Development with Digital Technology: An Analysis Framework Based on Schumpeter's Endogenous Growth Theory. *Management World, 38,* 56-74. https://doi.org/10.19744/j.cnki.11-1235/f.2022.0076

Wang, H. (2022). Characteristics of Equity Incentive Contracts and High-Quality Development of Companies. *Statistics and Decision, 38,* 175-179.

https://doi.org/10.13546/j.cnki.tjyjc.2022.05.034

Wang, R., & Zhang, H. (2023). Digital Transformation and Foreign Direct Investment of Enterprises: The Mediating Role of Innovation Capability and Transaction Costs. *Finance and Trade Research, 34,* 14-24. https://doi.org/10.19337/j.cnki.34-1093/f.2023.05.002

Wang, Y. (2020). The Great Transformation of a Century, High-Quality Development, and Building a New Development Pattern. *Management World, 36,* 1-13. https://doi.org/10.19744/j.cnki.11-1235/f.2020.0179

Wei, J., Ge, P., & Wang, J. (2017). Institutional Environment, Institutional Dependence, and Total Factor Productivity of Enterprises. *Statistical Research, 34,* 38-48. https://doi.org/10.19343/j.cnki.11-1302/c.2017.05.004

Wen, H., & Zhong, Q. (2022). Digital Infrastructure and Total Factor Productivity of Enterprises: Evidence from Listed Companies in China. *Soft Science, 36,* 64-71.

Wu, C., Zhang, K., Zhou, X. et al. (2022). Digital Transformation, Choice of Competitive Strategy, and High-Quality Development of Firms: From Evidence of Machine Learning and Text Analysis. *Business Management Journal, 44,* 5-22. https://doi.org/10.19616/j.cnki.bmj.2022.04.001

Wu, F., Hu, H., Lin, H. et al. (2021). Enterprise Digital Transformation and Capital Market Performance: Empirical Evidence from Stock Liquidity. *Management World, 37,* 130-144. https://doi.org/10.19744/j.cnki.11-1235/f.2021.0097

Yami, S., M'Chirgui, Z., Spano, C. et al. (2021). Reinventing Science and Technology Entrepreneurship Education: The Role of Human and Social Capitals. *Technological Forecasting & Social Change, 164,* Article 120044. https://doi.org/10.1016/j.techfore.2020.120044

Yang, R. (2015). Research on Total Factor Productivity of Manufacturing Enterprises in China. *Economic Research, 50,* 61-74. https://www.cnki.com.cn/Article/CJFDTOTAL-JJYJ201502006.htm

Ye, Y., Li, X., & Liu, G. (2022). Digital Transformation and Upgrading of Enterprise Human Capital. *Finance and Economic Research, 510,* 74-92. http://www.jryj.org.cn/CN/Y2022/V510/I12/74

Yuan, C., Xiao, S. S., Geng, C. X. et al. (2021). Digital Transformation and Enterprise Division of Labor: Specialization or Vertical Integration. *China Industrial Economics, No. 9,* 137-155. https://doi.org/10.19581/j.cnki.ciejournal.2021.09.007

Yuan, Y. (2017). BPR Is Born for Digital Transformation. *Enterprise Management, No. 10,* 102-104. https://www.cnki.com.cn/Article/CJFDTotal-QIGL201710042.htm

Zeng, D. Z., Shi, L., & Luetkenhorst, W. (2021). China's Green Transformation through Eco-Industrial Parks. *World Development, 140,* Article 105249. https://doi.org/10.1016/j.worlddev.2020.105249

Zhao, C., Wang, W., & Li, X. (2021). How Does Digital Transformation Affect Total Factor Productivity of Enterprises? *Finance and Trade Economics, 42,* 114-129. https://doi.org/10.19795/j.cnki.cn11-1166/f.20210705.001