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Impact of Enterprise Digital Transformation on Key Core Technology Innovation: The Mediating Effect of Total Factor Productivity

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Abstract

Digital transformation, by introducing a series of cutting-edge technologies, provides developmental trajectories and innovative pathways for key core technologies, which serve as strategic fulcrums of national competitiveness. This study uses data from listed high-tech manufacturing enterprises in 2014-2023 as its research sample to empirically examine the impact of digital transformation on key core new technology innovation and the mediating effect of total factor productivity. The findings indicate that digital transformation can significantly enhance innovation in key core technologies. Furthermore, analysis of the underlying mechanisms demonstrates that digital transformation can improve key core technology innovation by increasing total factor productivity. In this regard, this paper proposes the following recommendations: 1) Strengthen digital technology research and developemt (R&D) investment and enhance independent innovation capability. 2) Promote industrial digital transformation and foster coordinated development across upstream and downstream sectors. 3) Advance market-oriented reforms of factors and improve the efficiency of macroecnomic resource allocation.

Keywords

digital transformation, key core technology, total factor productivity, high-tech industry

1. Introduction

Against the background of intensified global competition and the in-depth development of the technological revolution, digital transformation has emerged as a core driver of socioeconomic change. It not only reshapes enterprises' business processes, market strategies and consumer experiences but also profoundly affects the developmental trajectories and innovation pathways of key core technologies.

As strategic fulcrums of national competitiveness, the independent controllability of key core technologies directly impacts the security of industrial chains and sustainable development. By introducing a series of cutting-edge technologies, digital transformation has provided unprecedented momentum and possibilities for the innovation and development of key core technologies. These emerging technologies have not only greatly enhanced the capabilities in data processing, storage and analysis but also promoted the efficient circulation and intelligent application of information. This creates vast opportunities for the upgrading of key core technologies, offering new pathways to address deepseated challenges such as the "chokepoint" risks in core technologies, cross-domain collaboration barriers, and issues related to technology ethics and security.

In recent years, theoretical analyses on digital transformation and key core technologies have been abundant, yet empirical analyses on the impact of digital transformation on key core technology innovation and its underlying mechanisms remain scarce. Considering the high dependence of high-tech enterprises on key core technologies, this paper takes the high-tech manufacturing industry as a case study to explore the impact and mechanisms of enterprise digital transformation on key core technology innovation. It aims to provide valuable insights and references for policymakers, researchers, and practitioners in related fields. .

2. Literature Review

2.1 Research on Digital Transformation

With respect to the concept and significance of digital transformation, Zeng et al. (2021) believe that digital transformation is a process that starts with the foundational support of digital technologies, digital products, and digital platforms and thus triggers changes at individual, organizational, and industrial levels. Zhu and Lin (2022)suggest that the outcomes of digital transformation include mainly new products, new services, new processes, and enterprise performance at the enterprise level; stakeholder satisfaction at the ecosystem level; and digital dividends, digital entrepreneurship, digital environments, and digital societies at the social level.

In terms of the significance of digital transformation, from an enterprise perspective, Huang et al. (2021) found through empirical research that digital transformation can significantly increase enterprise value, with this effect being particularly pronounced in high-tech enterprises. From a social perspective, digital transformation encourages enterprises to undertake greater social responsibilities (Zhao, 2022). Shang and Wu (2022) integrate the social and economic benefits of digital transformation, arguing that digital transformation mitigates the emergence of superficial social responsibility while achieving lean manufacturing and high-efficiency production through emerging digital technologies. This enhances enterprises’ capability to fulfill responsibilities and achieve value enhancement .

To measure digital transformation, Wu et al. (2021) constructed feature words related to digital transformation from corporate annual reports and measured digital transformation using text analysis by calculating keyword frequency. Zhao et al. (2021) used the expert scoring method to assess the extent of digital transformation on the basis of text analysis. Qi et al. (2020) and He and Liu (2019) measured the enterpruse’ digitization level by calculating the proportion of the part related to the digital transformation within the year-end intangible asset details disclosed in listed companies’ financial report notes relative to total intangible assets.

2.2 Research on Key Core Technologies

In recent years, domestic and international scholars have focused their research on key core technologies, encompassing their conceptualization, selection and identification, influencing factors and breakthrough pathways. Wang (2019) defines key core technologies as those that hold a central position and play a critical role in a specific industries or field during a specific historical period, comprising both key technologies and core technologies. Yang and Chen (2023) note that key core technologies exhibit attributes of high market entry barriers, evolutionary dynamics, and high-cost investment, making them an indispensable technical domain in enterprise competition.

At present, the selection and identification of key core technologies include both qualitative and quantitative mathods, such as the Delphi method, patent analysis, and bibliometric analysis. Zhang and Miao (2020)combined technology foresight with trend analysis to conduct in-depth research on the selection mechanisms for “chokepoint” key core technologies. Yang and Yang (2019) used patent data as an identification metric, constructing a core technology identification index system. They employed an optimal combination weighting method, integrating subjective and objective weighting approaches to determine index weights to develop a core technologiey evaluation index.

With respect to the influencing factors of key core technologies, Zhang et al. (2023)categorized them into two dimensions: enterprise characteristics, including R&D funding, independent innovation capability, and deep industry-academia-research integration; and external environment, encompassing market mechanisms, policy and institutional support systems, intellectual property protection systems, and technological infrastructure and service systems.

Concerning breakthrough pathways for key core technologies, Chen and Zhu (2020), grounded in the Chinese context, proposed a framework and strategy system to address the “chokepoint” challenges of key core technologies. This framework emphasizes leveraging “greatest advantage”, strengthening “dual coordination”, resolving “two major contradictions”, enhancing the “two types of capabilities”, deepening “dual integration” and reinforcing “two forms of support”. Hu and Yuan (2022) summarized the factors contributing to breakthroughs in key core technologies into seven aspects: awareness of technological suppression and demand orientation, international technological cooperation and open innovation, deep of industry-acdemia-research integration, sustained and sufficient R&D funding, leading talent and their collaborative teams, the technology and industrial chains, and government policies and institutional mechanisms.

2.3 Research on the Impact of Digital Transformation on Key Core Technology Innovation

With respect to the impact of digital transformation on key core technology innovation, existing studies generally believe that digital transformation promotes enterprise’s key core technologies. Through theoretical research, Guo et al. (2023) noted that the digital transformation of enterprises facilitates technological innovation. In terms of its mechanisms, Shi and Peng (2024) reported that digital transformation significantly enhances innovation efficiency, with mechanisms driven by knowledge breadth and Schumpeterian rents. Xi et al. (2025) suggested that by strengthening enterprise R&D cooperation and accelerating its integration into global innovation networks, digital transformation fosters open innovation models, thereby promoting breakthroughs in key core technologies. Meanwhile, Chen and Shi (2024) concluded through empirical research that enhancing the degree of enterprise digitalization levels promotes the innovation of key core technologies by promoting R&D investment.

Through a literature review, it evident that the connotations, outcomes, and implementation pathways of digital transformation have garnered significant academic attention. Similarly, the identification and breakthrough factors of key core technologies have been constantly enriched in the scholarly research, providing a robust foundation for this paper. However, empirical studies on the impact of enterprise digital transformation on key core technology innovation remain relatively scarce, with mechanisms yet to be fully developed, long-term tracking studies insufficient, and the sustainability of digital transformation still requiring validation. On the basis of the existing research, this study uses data from listed high-tech manufacturing companies from 2014 to 2023 as its sample and employed a two-way fixed effects model to examine the impact of digital transformation on key core technologies and the mediating effect of total factor productivity.

3. Research Hypotheses

3.1 Impact of Enterprise Digital Transformation on Key Core Technology Innovation

Through a series of technological and management changes, digital transformation has provided unprecedented opportunities and driving forces for the innovation of key core technologies. High-tech manufacturing enterprises are heaviy dependent on the degree of digital transformation, which serves as the foundational support for their technological innovation, business implementation, and market competitiveness. Without digital transformation, maintaining technological advantages and commercial value becomes challenging. First, through the introduction of advanced technologies such as cloud computing, big data, and artificial intelligence, digital transformation has greatly enhanced enterprises’ capabilities to process and analyze large volumes of complex data, thereby helping enterprises quickly identify market trends, consumer preferences and competitor dynamics while providing precise data support for technological R&D, thereby accelerating the R&D cycle of new technologies and improving the innovation efficiency of high-tech manufacturing enterprises (Yang et al., 2022). Second, digital transformation promotes the circulation and sharing of information both inside and outside the enterprise, breaking down barriers of traditional organizational structures. By building digital platforms and tools, enterprises can more easily achieve crossdepartmental and cross-regional collaboration, accelerating knowledge transfer and the integration of creative ideas. This efficient collaboration mechanism plays an important role in overcoming key technical challenges and developing new technologies. In addition, higher levels of digitization enable enterprises to make more scientific and precise decisions during the technological R&D process. Moreover, digital transformation not only enhances enterprises' willingness to take risks but also strengthens their risk-taking capabilities (Jiang, 2024), thereby ensuring the smooth progress of key core technology R&D. On this basis, the following hypothesis is proposed:

H1: Digital transformation has a positive impact on key core technology innovation in high-tech enterprises.

3.2 Mediating Role of Total Factor Productivity

Total factor productivity (TFP) is a core indicator for measuring technological progress and efficiency improvements, representing the additional output growth driven by factors such as technological progress, organizational innovation, specialization and production innovation, beyond the contributions of tangible inputs such as capital and labor. Key core technologies often serve as the tangible embodiment and ultimate outcome of these "intangible factors". Therefore, TFP is highly important in studying the relationship between digital transformation and key core technology innovation. First, the research by Guo and Wang (2022) shows that enterprise digital transformation promotes the application and diffusion of digital technologies, which integrate with existing production factors and processes to optimize workflows and reduce resource waste, thus enchancing TFP. The increase in TFP further promotes breakthroughs in key core technology innovation. Second, the R&D of key core technologies is characterized by high investment, long cycles, and high failure rates. Digital transformation, through big data analytics, enhances the scientific rigor of managerial decision-making, reduce trial-and-error costs, and thus improves TFP. An economic system or enterprise with high TFP achieves greater output with fewer resource inputs, thus creating higher profits and greater "resource redundancy", which provides a solid financial foundation for enterprises and nations to undertake the long-term and uncertain R&D investments required for key core technologies. In the end, when the marginal benefits brought by traditional factor inputs diminish, the inherent need to pursue higher TFP "induces" enterprises and economies to shift their focus toward technological innovation, especially toward key core technologies that can drive disruptive efficiency improvements. On this basis, the following hypothesis is proposed:

H2: Total factor productivity plays a positive mediating role in the impact of digital transformation on key core technology innovation; that is, digital transformation enhances key core technology innovation by promoting TFP.

4. Research Design

4.1 Variable Selection

4.1.1 Dependent Variable

Key Core Technology (KCT) Innovation: At present, academic approaches to measuring key core technology innovation in academia include expert judgement methods, single-indicator identification methods, indicator system identification methods, and patent co-classification methods. However, the above methods have limitations in terms of comprehensiveness and practicability. In this study, in reference to the approach of Wu and Yan (2023), five indicators, i.e., patent quantity, quality, impact, novelty, and originality of patents, are constructed to measure the innovation performance of enterprises in key core technology domains. The raw patent data are sourced from the State Intellectual Property Office of China (Yang et al., 2021). "The Catalog of Industrial Base Innovation and Development (2021 Edition)" issued by the National Strategy Committee for Building a Manufacturing Power, details 1,047 specific technologies across 21 key core technology domains. In the course of the research, in reference to the methodology of Zheng et al. (2024), the keywords of these 1047 key technologies with the patent descriptions corresponding to the five-level codes of the International Patent Classification (IPC) are precisely matched. This process identifies the IPC codes associated with patents in these key core technology domains, and finally, the annual patent application counts for enterprises in these domains are then aggregated.

4.1.2 Independent Variable

Digital Transformation (DT): Digital transformation represents technological upgrades and organizational cultural changes. The use of the text analysis methods can efficiently and systematically extract key information from unstructured textual data, compensating for the deficiencies of traditional quantitative methods while accommodating the dynamic, complex and implicit characteristics of digital transformation. In accordance with the practices of Wu et al. (2021), this paper uses Python web-crawling techniques to obtain annual reports of listed high-tech manufacturing companies. Drawing on national policy texts, 47+60 characteristic keywords related to digital technology applications and business model innovation were identified. These keywords are matched and counted against the text of the enterprise's annual report to calculate the total word frequency. Owing to the right skewed nature of this data, a logarithmic transformation is taken after adding 1 to the values, yielding an indicator of the digitization level for listed high-tech manufacturing enterprises.

4.1.3 Mediating Variable

Total Factor Productivity (TFP): It refers to the additional economic value generated per unit of input, representing efficiency increase in the production process that cannot be directly explained by traditional production factors such as land, capital and labor. In essence, it is a comprehensive reflection of "soft power" elements, including technological progress, organizational innovation, and resource allocation optimization. Therefore, TFP serve as a critical macroeconomic environment and economic foundation that nourish and catalyze of key core technology innovation. By generating economic surplus, cultivating high-end talent and optimizing innovation ecosystems, TFP provides the essential resources, capabilities and market environment necessary for breakthroughs in key core technologies. Moreover, the continuous pursuit of higher TFP provides sustained motivation and clear direction for core technology R&D. For the measurement of TFP, this paper adopts the approach of Lu and Lian (2012), controlling for industry, year, and region to derive the TFP calculation formula:

$$TFP_{i,t} = \ln Y_{i,t} - \beta_k \ln K_{i,t} - \beta_i \ln L_{i,t} \tag{1}$$

where Y represents the added value of output, K represents capital input, L represents labor input, and β_k and β_l represent the output elasticities of capital and labor, respectively (Wu and Yan, 2023).

4.1.4 Control Variables

This study posits that in addition to digital transformation, many other factors affect key core technology innovation. To ensure the accuracy of the empirical results, the following control variables areselected: asset-liability ratio, return on total assets, fixed assets ratio, current ratio, and financial leverage. The specific definitions of each variable are shown in Table 1.

Table 1: Variable Definitions

Variable	Variable Name	Variable Symbol	Variable Description
Dependent Variable	Key Core Technology Innovation	KCT	Number of patent applications in key core technology domains
Independent Variable	Digital Transformation	DT	Logarithm of the frequency of digitalization-related keywords in enterprise annual reports +1
Mediating Variable	Total Factor Productivity	TFP	Difference after logarithmic transformation of output value added, capital marginal output, and labor marginal output
Control Variables	Asset-Liability Ratio	LEV	Total liabilities/total assets
	Return on Total Assets	ROA	Net income at period-ed/average total assets
	Fixed Asset Ratio	Fixed	Net fixed assets/total assets
	Current Ratio	CR	Current assets/current liabilities
	Financial Leverage	LFP	Earnings before interest and taxes/(earnings before interest and taxes - financial expenses)

4.2 Model Specification

With respect to the impact of digital transformation on key core technology innovation, the following baseline model is constructed:

$$KCT_{i,t} = \alpha_0 + \alpha_1 DT_{i,t} + \alpha_2 Control_{i,t} + \mu_i + \gamma_t + \varepsilon_{i,t} \quad (2)$$

To test the mediating pathway, the following mediation model is established:

$$TFP_{i,t} = \beta_0 + \beta_1 DT_{i,t} + \beta_2 Control_{i,t} + \mu_i + \varepsilon_{i,t} \quad (3)$$

In the above two models, α and β represent the parameters to be estimated; KCT denotes key core technology innovation, the dependent variable of this study; TFP represents total factor productivity, the mediating variable; DT indicates the level of enterprise digital transformation; Control encompasses a series of control variables; μ represents individual fixed effects; γ represents time fixed effects; and ε indicates the random error term.

4.3 Data Sources and Descriptive Statistics

This study is based on the industry codes from the "Guidelines for the Industry Classification of Listed Companies" (revised in 2012) by the China Securities Regulatory Commission (CSRC) and selected China's 2014–2023 A-share listed companies in the following sectors: computer, communications and other electronic equipment manufacturing; pharmaceutical manufacturing; railway, ship, aerospace, and other transportation equipment manufacturing; and instruments and meters manufacturing. These sectors represent high-tech manufacturing industries. The samples were processed as follows: 1) companies labeled as ST or *ST were excluded; 2) Companies with excessive missing data or incomplete disclosures regarding digital transformation and key core technologies were removed; 3) All continuous variables were winsorized at the 1st and 99th percentiles to eliminate extreme values. After processing, a total of 1460 observations were obtained. In this paper, the digital transformation data were from corporate annual reports, the key core technologies data were from the State Intellectual Property Office of China, and the remaining data were from the China Stock Market & Accounting Research (CSMAR) database. Table 2 lists the descriptive statistics of the variables.

Table 2: Descriptive Statistics Results

Variable	Observations	Mean	Standard Deviation	Maximum	Minimum
KCT	1460	27.780	116.623	1812	0
DT	1460	2.481	1.237	5.768	0
TFP	1460	8.464	0.995	11.473	4.521
LEV	1460	0.362	0.165	0.858	0.052
ROA	1460	0.045	0.063	0.234	-0.672
Fixed	1460	0.191	0.124	0.586	0.002
CR	1460	2.878	2.506	18.226	0.542
LFP	1460	1.304	2.173	48.739	-8.998

5. Empirical Analysis

5.1 Benchmark Regression Analysis

To test the impact of enterprise digital transformation on key core technology innovation, and thereby verify Hypothesis H1, regression analysis was conducted using Equation (2). The results are shown in Table 3. The regression results without control variables are listed in (1), where the regression coefficient of digital transformation on key core technology innovation is 5.111, statistically significant at the 5% level. The regression results with the control variable are added in Column (2), showing a regression coefficient of 4.873, also statistically significant at the 5% level, indicating robust results. Therefore, enterprise digital transformation has a significant positive effect on key core technology innovation, consistent with the expectations of Hypothesis H1.

Table 3: Benchmark Regression of Digital Transformation on Key Core Technology Innovation

	(1)	(2)
	KCT	KCT

DT	5.111**	4.873**
	(2.27)	(2.20)
LEV		7.004
		(0.53)
ROA		-27.81
		(-1.60)
Fixed		13.63
		(0.76)
CR		0.412
		(0.79)
LFP		0.891
		(1.42)
_cons	7.075	1.401
	(0.91)	(0.12)
N	1460	1460
R2	0.0174	0.0196

*Note: *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively. Values in () are t-statistics. The same applies to subsequent tables.*

5.2 Mediation Mechanism Analysis

To test the positive mediating role of TFP in the impact of digital transformation on key core technology innovation, thereby verifying Hypothesis H2, regression analysis was conducted using Equation (3). The results are shown in Table 4. The regression results without control variables are listed in Column (1), where the regression coefficient is consistent in direction with the baseline regression model. The regression results with control variables are added in Column (2), showing a regression coefficient of digital transformation on TFP of 0.177, statistically significant at the 1% level. Combined with the inducing effect of increased TFP on key core technology innovation,. these results indicate that TFP plays a positive mediating role in the impact of digital transformation on key core technology innovation; that is, digital transformation enhances key core technology innovation by promoting TFP, consistent with the expectations of Hypothesis H2.

Table 4: Mediating Effect of Total Factor Productivity

	(1)	(2)
	TFP	TFP
DT	0.210***	0.177***
	(7.21)	(5.85)
LEV		0.639**
		(1.99)
ROA		1.331***
		(4.30)
Fixed		-2.583***
		(-6.79)
CR		-0.0581**
		(-2.08)
LFP		0.00602
		(1.19)
_cons	7.944***	8.385***
	(110.22)	(33.36)
N	1460	1460
R2	0.125	0.318

5.3 Endogeneity Test

Given that digital transformation may be affected by the error term, potentially leading to endogeneity bias in the estimation results for key core technology innovation, this study addresses this problem by introducng the one-period lagged value of key core technology innovation as an instrumental variable and using the system generalized moments (SYS-GMM) for regression estimation. The test results are listed in Table 5. The positive effect of digital transformation on key core technology innovation is statistically significant at the 1% level. The p-value for the AR(1) test is less than 0.1, and the p-value for the AR(2) test is greater than 0.1, indicating that the difference disturbance term exhibits no second-order autocorrelation. Therefore, the null hypothesis that the disturbance term has no autocorrelation is accepted. The p-value of the Hansen test is 0.139, confirming the validity of the selected instrumental variable and effectively resolving the endogeneity problem.

Table 5: Endogeneity Test Results

Variable	Dependent Variable KCT
L. KCT	0.839*** (31.09)
DT	46.769*** (3.15)
Control Variables	Controlled
Firm Effects	Controlled
Year Effects	Controlled
AR(1) P-value	-2.45 0.014
AR(2) P-value	-0.78 0.436
Hansen test	62.01
P-value	0.139

*Note: *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively. Values in () represent z-statistics.*

5.4 Robustness Tests

To test the robustness of the regression results of the impact of enterprise digital transformation on key core technology innovation, this study uses two methods, namely, adding control variables and adjusting the sample period, to enhance the reliability of the regression results. First, financing constraints are added as an additional control variable, measured using the KZ index, with results shown in Columns (1) and (2) of Table 6. Next, the sample from 2014 is excluded to test whether changing the sample period affects the baseline regression results, with findings shown in Columns (3) and (4) of Table 6. The empirical results indicate that the direction of the regression coefficients remains unchanged and statistically significant after incorporating the additional control variable and adjusting the sample period. These results prove that the empirical results for digital transformation and key core technology innovation in Table 3 are reliable and robust.

Table 6: Robustness Test Results

	(1)	(2)	(3)	(4)
	KCT	KCT	KCT	KCT
DT	5.111** (2.27)	4.835** (2.20)	5.211* (1.90)	5.040* (1.85)
Control variables	Not controlled	Controlled	Not controlled	Controlled
Firm Effects	Controlled	Controlled	Controlled	Controlled
Year Effects	Controlled	Controlled	Controlled	Controlled
_cons	7.075	-0.0541	10.08	9.567
	(0.91)	(-0.00)	(1.19)	(0.88)
N	1460	1460	1314	1314
R2	0.0174	0.0197	0.0140	0.0163

*Note: *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively. Values in () represent t-statistics.*

6. Conclusions and Recommendations

6.1 Main Conclusions

This study focuses on 2014–2023 high-tech manufacturing enterprises and employs a two-way fixed effects model to examine the impact of enterprise digital transformation on key core technology innovation. The following conclusions are drawn: (1) The benchmark results show that enterprise digital transformation significantly enhances the innovation and development of key core technologies. These findings are robust, having passed endogeneity tests using the one-period lagged value of the dependent variables, as well as robustness tests involving additional control variables and and adjustments to the sample period, confirming the reliability of the results. (2) The mediation analysis reveals that total factor productivity plays a positive mediating role in the impact of digital transformation on key core technology innovation; that is, digital transformation can promote key core technology innovation by increasing TFP.

6.2 Recommendations

First, investment in digital technology R&D and independent innovation capacity should be strengthened. Governments should increase funding for basic and applied research in digital technologies for high-tech enterprises, establishing specialized research funds to prioritize key core technology domains such as industrial big data and artificial intelligence. Encourage the formation of collaborative innovation alliances among universities, research institutions and enterprises to accelerate the transformation of research outcomes into practical applications, enhance independent innovation capabilities, and reduce reliance on foreign key core technologies.

Second, industrial digital transformation and coordinated development across supply chains should be promoted. Encourage leading enterprises in the industry to play a pivotal role in driving the participation of small and medium-sized enterprises within the supply chain to participate in digital application scenarios and ecosystem development. This addresses the issue of the uneven digital transformation levels among enterprises, enhancing the overall digitalization level and collaborative efficiency of supply chains.

Third, enhance factor market reforms and macro-level resource allocation efficiency. Governments should deepen the market-oriented reforms for the allocation of factors such as capital, land, labor, and technology, enabling these factors to flow from less efficient sectors to more efficient ones, particularly strategic emerging industries. Moreover, ensure orderly market competition and the free factor mobility to guarantee that resources are allocated to the most efficient sectors and fields.

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