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A Mechanistic Examination of the Impact of Digital Transformation on the Performance of Chinese Manufacturing Firms: An Analysis of the Mediating Role of Firm Innovation

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Abstract

With the digital economy serving as a key driver of global economic growth, this study aims to investigate the impact of digital transformation on total factor productivity in manufacturing enterprises. Using Chinese A-share listed manufacturing enterprises as a sample from 2013 to 2020, we constructed a digital transformation index through text analysis. We conducted empirical analysis using a two-way fixed effects model. The empirical study demonstrates that digital transformation has a significant impact on total factor productivity, and this conclusion remains robust following rigorous testing. The mechanism analysis confirms that innovation capacity is a key mediating variable, indicating that digital transformation indirectly promotes productivity growth by strengthening enterprise innovation capacity. Heterogeneity analysis further reveals that: (i) the application of digital technology has a more substantial effect on total factor productivity than digital business models; (ii) enterprises located in eastern regions, in highly competitive industries, classified as non-state-owned enterprises or high-tech enterprises, and with dual roles have more significant productivity gains. The contribution of this study lies in its use of innovation capacity as a core mediating variable to reveal the 'black box' mechanism of digital-driven efficiency improvement, providing new microeconomic insights into the impact of digital transformation on total factor productivity. In addition, heterogeneity analysis from multiple dimensions, including digital dimensions, external characteristics, and internal characteristics, systematically presents the boundary conditions of the transformation effect, providing practical inspiration for different types of manufacturing enterprises to formulate digital strategies and improve total factor productivity.

Keywords: *digital transformation; total factor productivity; manufacturing industry; innovation ability*

1 Introduction

The deep application of digital technologies such as cloud computing, big data, artificial intelligence, and the Internet of Things in the manufacturing sector not only represents technological innovation but also brings profound systemic changes to the manufacturing industry, including the restructuring of production models, organizational structures, business processes, and even the entire value chain. Digital transformation helps manufacturing enterprises integrate and optimize production factors, enhancing synergies and becoming a new engine for total factor productivity (TFP) growth. As a core indicator for measuring technological progress, resource allocation efficiency, and overall management improvement, TFP is a powerful driver of economic growth (Solow, R. M, 1957). Therefore, it has long been the focus of economic research. At the macro level, Guo Jitao et al. (2021) and Pan et al.(2022) have shown that the development of the digital economy has significantly improved TFP. At the level, scholars such as Liu Pingfeng et al. (2021) have pointed out that digital transformation enhances manufacturing productivity through capital-empowering and labor-empowering technologies, while Song Wei et al. (2022) emphasize the significant improvement of industrial TFP by data elements. Some studies have also shown that digital transformation has a positive impact on stock liquidity and input-output efficiency (Wu, F et al, 2021 and Liu Shuchun et al, 2021), but some studies point out that it may lead to inefficient R&D (Jacobides et al, 2018). In addition, scholars have observed the ' over-digitalization' effect, whereby excessive digitalization may bring meagre returns or even hurt business performance (Feifei et al, 2022). There are differing views in academia on the impact of digital transformation. Therefore, an in-depth study of the impact of digital transformation on total factor productivity (TFP) in Chinese manufacturing enterprises is not only of practical significance but also provides empirical evidence for theoretical research.

2 Literature Review and Research Hypothesis

Transaction cost theory posits that firms incur various costs during market transactions, including information gathering, customer coordination, pricing decisions, negotiation processes, property rights confirmation, and contract enforcement (Li Weian and Hao Chen, 2017). However, the digital transformation driven by technologies such as the Internet, big data, artificial intelligence and blockchain has eliminated time and space constraints on transactions, enabling complex transactions to be completed directly online. Simplified communication channels and expanded sources of information have significantly reduced transaction costs. Transactions that previously required internal processing can now be executed efficiently in the market (Chen Dongmei et al, 2017). Lately, studies across the industry and at the company level have shown strong links between embracing digital technology and improved productivity (Dedrick et al, 2003 and Syverson, 2011). Loebbecke and Picot (2015) particularly highlighted that leveraging big data analytics can greatly streamline corporate decision-making, cutting down on valuable time and enhancing overall operational prowess. Qi Yudong and Cai Chengwei (2019) highlighted that in the big data era, production and consumption processes generate massive amounts of data. Effective utilization of this data can significantly enhance productivity through strategic decision-making and operational optimization. He Fan and Liu Hongxia (2019) demonstrated that digital transformation reduces corporate costs while improving asset utilization efficiency. Furthermore, digital transformation leaders' implementation of technologies such as smart manufacturing, real-time monitoring systems, automated quality control, efficient logistics networks, and AI-powered HR solutions has substantially boosted production efficiency. Based on this data, the research posits a positive correlation between digital evolution and overall productivity.

H1: Digital transformation has a positive impact on total factor productivity.

First, digital transformation drives productivity growth through enhanced innovation capabilities. Abernathy et al. (1978) posited that while productivity gains are crucial for corporate success, long-term sustainability requires both efficiency improvements and innovative capacity. Brynjolfsson et al. (2011) analyzed the rapid productivity growth of U.S. firms since the mid-1990s, revealing how data-driven decision-making enabled real-time tracking of innovation models. This digitalization accelerated the spread of innovations via internet platforms, driving improvements in business models and production processes. Huang Qunhui et al. (2019) demonstrated that internet technology reduced transaction costs and minimized resource misallocation, fostering industrial specialization that spurred corporate innovation and productivity growth. Secondly, digital transformation boosts productivity through enhanced absorptive capacity. Guo Hai and Han Jiaping (2019) argued that digital technologies improve Chinese open innovation by strengthening enterprises' ability to integrate external knowledge and information, thereby enhancing their capacity to process and adopt new technologies and knowledge. This technological advancement ultimately elevates corporate productivity. Ultimately, digital transformation fosters productivity growth by enhancing adaptability. Guo Hai and Han Jiaping (2019) argue that digital technology adoption will significantly influence China's open innovation landscape. Their reasoning stems from how digital tools enhance firms' capacity to process external information and knowledge, thereby boosting organizational learning and operational flexibility. This technological integration ultimately drives productivity gains across enterprises. Building upon these insights, the researchers formulate their hypotheses.

H2: Digital transformation improves total factor productivity by improving the innovation capacity of enterprises.

Digital transformation juices up overall productivity by fine-tuning the human capital game. As manufacturing gets more complex, we're seeing a real push for specialized roles. A top-notch workforce and niche expertise grease the wheels, smoothing out connections across the value chain (Sun Xiangxiang and Zhou Xiaoliang, 2018). This not only streamlines how companies do things but also slashes production and transaction costs, solidifying their spot in the industrial pecking order. Smart companies are swapping out less-skilled workers for cutting-edge tech, and the demand for brainpower is only going up, leading to a smarter, leaner workforce (Sun Zao and Hou Yulin, 2019). When you pump up the human capital, injecting high-quality knowledge into the mix, you get a tech domino effect that seriously boosts innovation (Liu, W. G and Ni, H. F, 2018). This pushes companies to aim high, focusing on both the high-value design and marketing ends of the spectrum, while constantly looking for ways to cut costs and work smarter. Building on this, we're putting forward Hypothesis 3.

H3: Digital transformation can optimize the structure of human capital and improve the total factor productivity of enterprises through the spillover effect of knowledge capital and human capital.

3 Research Design

3.1 Data sources and sample selection

This study began by collecting initial data from Chinese A-share listed manufacturing firms, covering the period from 2013 to 2020. Because this timeframe aligns with the development process of China's digital economy policies, and considering data updates, 2020 has been set as the cut-off year. Following standard practices, samples with missing data from the financial and insurance sectors were excluded. Additionally, software and information technology companies were excluded because of their close association with informatization, which would obscure the dynamic impacts of digitalization. To mitigate outlier effects, all continuous variables underwent bilateral trimming at the 1st percentile quantile, while logarithmic transformation was applied to certain variables to address heteroskedasticity. Data on finances originate from the CSMAR repository, while patent information comes from the CNRDS archive.

3.2 Description of main variables

(1) The dependent variable

This research adopts the methodology outlined by Ren et al. (2013), utilizing linear programming (LP) to assess Total Factor Productivity (TFP). The LP technique was selected for its ability to circumvent problems like sample attrition and endogeneity biases. Total output is quantified through core business revenue, while net fixed assets gauge capital input. Labor input is derived from employee wages and benefits, with intermediate inputs computed as follows: (operational costs + sales expenditures + administrative expenses + financial charges - depreciation - employee compensation). The final productivity figures are then transformed using natural logarithms for analysis.

(2) Explanatory variables

The independent factor investigated is the Digital Transformation process (DIGI). Following the research methodology of Wu F. et al. (2021), we employed text analysis to construct a Digital Transformation Index through word frequency statistics. Specifically, we first extracted digital transformation-related keywords from "Made in China 2025", historical Government Work Reports, and relevant news and conference materials. Building on this foundation, we supplemented the keyword lexicon by referencing studies by Wu F. et al. (2021), Zhao, C. Y. (2021), and Qi Yudong et al. (2019). Ultimately, we established a key term database for manufacturing enterprises' digital transformation, focusing on two dimensions: digital technology application and digital business models, as shown in Table 1. The process for developing the digital transformation index unfolds in several key stages: initially, annual reports from Shanghai and Shenzhen A-share manufacturing firms (2013–2020) are gathered using Python-based web scraping techniques. These documents are then converted into TXT files through Xunjie PDF Converter for further analysis; second, extract all text content of the annual reports for text analysis and supplement the keywords with reference to relevant studies to build a keyword lexicon; third, perform word segmentation on the text of the enterprise annual reports based on the constructed keyword lexicon and count the disclosure frequency of keywords from the two dimensions of digital technology and digital business model; fourth, compute the corporate DX index: log (annual report DX keyword count + 1).

Table 1. Dimensions and keywords of digital transformation of manufacturing enterprises

Dimension	keyword
Digital technology applications	Artificial intelligence (AI), behavior recognition system (BI), distributed control system (DCS), fixed asset equipment management system (DT), electronic design automation (EDA), network public relations system (EPR), enterprise resource planning system (ERP), geographic information system (GIS), distributed system infrastructure (Hadoop)Human Resource Management (HRM), Manufacturing Execution System (MES), Management Information System (MIS), Financial Information Management System (NC), Office Automation System (OA), Oracle Database Management System, Product Lifecycle Management (PLM), Robotic Process Automation (RPA), Enterprise Resource Planning (SAP), Intelligent Manufacturing Innovation Platform (U9), Electronic Asset Security System (EAS), Information Technology (IT), Industrial Internet, and Industrial Robots
Digital business models	(SaaS), online, offline, ecological coordination, online retail, O2O, B2B, C2C, B2C, C2B, e-commerce, e-commerce

Source: Author Wu Fei, Zhao Chenyu, and Qi Yudong & Cai Chengwei

(3) Mediating variables

Innovation Potential (IP): Drawing on the methodology established by Li Chuntao et al. (2020), we measure innovation potential using the natural logarithm of patent counts—encompassing inventions, utility models, and design patents, whether filed independently or collaboratively.

Human Capital (Human): In line with the framework adopted by Zhao Chenyu et al. (2021), we operationalize human capital as the share of employees holding at least a bachelor's degree. This serves as a reliable indicator of workforce skill levels.

(4) Control variables

The study adopted the methodological framework outlined by Wu, F. et al. (2021) and colleagues. Key control variables—such as financial leverage (Lev), company size (Size), firm age (Age), liquidity measured by current asset turnover (Liq), and equity concentration (Share)—were drawn from Li Qi's earlier work (Li Qi et al, 2021). A comprehensive breakdown of these variables, including their precise definitions, can be found in Table 2.

Table 2. Variable description and calculation method

	Variable name	Meaning	Account form
Explained variable	TFP_{it}	Total factor productivity	LP algorithm
Explanatory variable	$DIGI_{it}$	Digital transformation index	Logarithm of digitized word frequency plus 1
Metavariable	*IP*	innovation ability	Natural logarithm of the number of patents
	Human	human capital	The proportion of employees with bachelor's degree or above
Controlled variable	*Lev*	degree of financial leverage	Total liabilities/total assets
	Size	scale	Natural logarithm of total assets of a firm
	Age	enterprise age	Observation year-establishment year
	Liq	Enterprise growth	Net main business income/average total current assets
	Share	Equity concentration	The sum of the shareholding ratio of the top 5 shareholders

Source Author

3.3 Model specification

According to the above theoretical analysis, this paper sets up the following benchmark regression model:

$$TFP_{it}=\alpha+\beta DIGI_{it}+\gamma Controls_{it}+\varphi_i+\delta_t+\varepsilon_{it} \quad (1)$$

In this model, i and t represent enterprises and years respectively; TFP_{it} denotes the total factor productivity level of enterprises; $DIGI_{it}$ indicates the digital transformation index for manufacturing enterprises; $\gamma Controls_{it}$ represents control variables; φ_i stands for individual fixed effects; δ_t denotes time fixed effects; ε_{it} represents random errors. β reflects the impact effect of digital transformation on total factor productivity. If β> 0 and statistically significant, it suggests that the digital transformation of manufacturing enterprises significantly enhances total factor productivity.

4 Analysis of Empirical Results

4.1 Descriptive analysis

Table 3 outlines the statistical breakdown of core variables. The total factor productivity (TFP) scores, serving as the dependent variable, span from a low of 4.32 to a high of 12.578—a clear reflection of the wide disparities in both developmental stages and operational efficiency across China's A-share listed firms. Meanwhile, the Digital Transformation Index (DIGI), our key explanatory variable, reveals a spectrum ranging from zero to 4.043, demonstrating that while some companies have adopted digital modernization, others have yet to join the bandwagon. This gap highlights the uneven adoption of technological upgrades within the market. Even those that have started the process exhibit varying degrees of progress, with overall implementation levels remaining relatively low and considerable room for improvement. Additionally, all control variables fall within reasonable distribution ranges.

Table 3. Descriptive statistics of variables from 2013 to 2020

Variable	Symbol	Mean	S.D.	Min	Max	Ob.
Total factor productivity	TFP_{it}	8.155	0.946	4.320	12.578	7992
Digital transformation index	$DIGI_{it}$	1.59	1.06	0	4.043	7992
Human capital	Human	0.220	0.161	0	0.748	7992
Innovation ability	IP	0.188	0.074	0	0.378	7992
Degree of financial leverage	Lev	0.392	0.181	0.055	0.779	7992
Scale	Size	22.304	1.175	20.195	24.1271	7992
Enterprise age	Age	17.496	5.475	4	53	7992
Turnover of current assets	Liq	0.567	0.139	0.335	0.779	7992
Equity concentration	Share	50.862	13.345	28.149	74.949	7992

Source: Authors' calculations using CSMAR data，CNRDS data and and textual mining of annual reports (SSE/SZSE A-share manufacturers).

4.2 Analysis of the effects of digital transformation on the total factor productivity of enterprises

4.2.1 Analysis of benchmark regression results

Drawing on a two-way fixed effects framework, this study examines the impact of digital transformation on total factor productivity (TFP) using data from China's A-share manufacturing firms between 2013 and 2020. As presented in Table 4, the findings offer compelling evidence of this relationship.

Model (1), which accounts for both firm-specific and temporal factors while including relevant controls, yields a statistically significant coefficient of 0.012 ($p<0.05$) for digital transformation. In practical terms, this means that for every point increase in a manufacturing firm's digital transformation score, its TFP rises by 0.012 units. Taken together, these results underscore the robust, productivity-boosting role of digital transformation across the manufacturing sector.

The analysis of control variables further reveals intriguing patterns. Notably, financial leverage shows a coefficient of 0.149 ($p<0.01$), suggesting that Chinese manufacturers experience rising TFP as they take on greater financial leverage. This finding aligns with broader trends in the industry's evolving economic landscape. Larger financial leverage equates to more abundant corporate capital, enabling technological upgrades and enhanced TFP. The figures suggest a positive link between the size of the business and its financial strength, with a statistical significance of 1%. This implies that bigger companies have access to more cash and tend to operate more efficiently. Moreover, scale effects become more pronounced in larger enterprises, further boosting TFP. Estimated firm age shows a significant, positive relationship at the 0.01 level (coefficient: 0.029). As enterprises mature, they refine management practices, adjust business operations, and refine organizational structures. These processes enhance resilience against external shocks, improve resource allocation efficiency, and develop more comprehensive strategic plans—all positively impacting TFP. The coefficient for the current asset turnover rate yields a significant positive correlation at the one percent level (0.438). This suggests that when companies manage their assets efficiently, it’s not just about avoiding operational pitfalls; it’s also about maximizing the return on their investment in terms of asset utilization. This, in turn, significantly boosts their total factor productivity (TFP). Notably, equity concentration—measuring shareholder control over enterprises—exhibits no significant impact on TFP under strengthened constraint conditions. However, from the perspective of individual capabilities, most current corporate development strategies are controlled by professional managers, while shareholders do not directly participate in actual business operations. The degree of equity concentration has little to no meaningful impact on a company's day-to-day operations, which explains why there's no statistically significant correlation with total factor productivity.

Table 4. Regression results on the impact of digital transformation on total factor productivity

Variable	TFP
DIGI	0.012** (2.509)
Lev	0.149*** (3.753)

Note: *, **, and *** indicate that the results are significant at the 10%,5%, and 1% significance levels, respectively. The T values are in parentheses.

Source: Authors' calculations using CSMAR data and textual mining of annual reports (SSE/SZSE A-share manufacturers).

Continuation of Table 4. Regression results on the impact of digital transformation on total factor productivity

Variable	TFP
Size	0.157*** (13.770)
Age	0.029*** (14.044)
Liq	0.438*** (10.309)
Share	0.022 (0.873)
Cons	9.699*** (39.094)
Individual effects	control
Time effect	control
N	7,992
R^2	0.279

Note: *, **, and *** indicate that the results are significant at the 10%,5%, and 1% significance levels, respectively. The T values are in parentheses.

Source: Authors' calculations using CSMAR data and textual mining of annual reports (SSE/SZSE A-share manufacturers).

4.2.2 Heterogeneity analysis

This study's benchmark regression examines the productivity-enhancing effects of digital transformation across manufacturing enterprises under full sample conditions. The analysis reveals asymmetric effects in productivity improvement due to variations in external characteristics (including differences in digitalization dimensions, regional and industry competition levels) and internal features (such as ownership structures, technological attributes, and organizational autonomy). To address this, we further segmented the sample using panel data from 2013-2020, estimating and comparing regression results across sub-samples.

4.2.2.1 Digital dimension heterogeneity

When we look at enterprise digital transformation, we can break down digital indicators into two main areas: how well they're using digital tech and how innovative their digital business models are. Now, if you glance at columns (1) and (2) in Table 5, you'll see that the digital tech application coefficient is roughly 0.012, which is statistically significant at the 10% level. In layman's terms, for every notch up a manufacturing company scores in applying digital tech, their total factor productivity gets a 0.012 boost. On the other hand, the digital business model coefficient hovers around 0.001, which is not statistically significant, meaning it does not significantly impact the outcome. Therefore, applying digital technology is the primary driver for manufacturing companies to achieve greater value through digital transformation, rather than the business model aspect. The thinking here is that technologies like big data and smart manufacturing are giving businesses a competitive edge across the board, from enhancing R&D to streamlining production and even boosting sales, through various avenues (Wu Qun, 2017). Fundamental business reforms are essential to stimulate innovative business models. Digital technologies enhance corporate insights into operational processes, transforming value creation methods while necessitating adjustments in service relationships, supply networks, and profit models. Digital business models enable companies to leverage technology to streamline their supply chains, refresh partnerships, and enhance service quality. However, while digital technology is the bedrock for revamping business models, simply relying on these models alone won't magically unlock maximum productivity. Given that digital business models represent a more mature stage of digital evolution, it suggests that China's manufacturing scene is still in the early stages of digital transformation, meaning there's plenty more to explore when it comes to these models. In short, the impact of digital transformation on overall productivity isn't one-size-fits-all. To be precise, digital transformation driven by the nuts and bolts of digital tech has a more noticeable impact on productivity compared to just implementing digital business models.

4.2.2.2 External characteristic heterogeneity of enterprises

The sample enterprises were categorized by region into eastern and central-western regions, with sample sizes of 5,616 and 2,376, respectively. The data presented in Table 5 (columns 3 and 4) reveal a statistically significant relationship between digital transformation and productivity in eastern enterprises, with a coefficient of 0.015 at the 5% significance level. Put simply, when manufacturing firms in eastern regions boost their digital transformation index by one point, their total factor productivity rises by 0.015. Interestingly, this effect doesn't hold water for companies in central-western areas—the numbers show no meaningful impact. This stark contrast suggests that digital transformation has a significantly greater impact on productivity gains for Eastern enterprises. This study posits that regional economic development levels influence the progress of digital transformation. Central-western regions face relatively underdeveloped digital infrastructure and lower adoption rates of digital technologies, which significantly constrain the vitality of local digital economies (Zhang Guosheng et al, 2021). These factors substantially reduce the enthusiasm and effectiveness of digital transformation initiatives among central-western enterprises. Consequently, the substantial gap in digitalization levels between eastern and central-western enterprises leads to significant differences in productivity-enhancing effects.

In contrast, eastern regions boast higher economic development levels and earlier digital transformation initiatives. Eastern enterprises demonstrate greater acceptance of emerging technologies like digital transformation and possess stronger financial and technological support for innovation exploration. Therefore, digital transformation in eastern enterprises exhibits more pronounced productivity-enhancing effects on total factor productivity.

The dataset was divided into two distinct industry categories—low-competition and high-competition—determined by their market concentration metrics, comprising 6,552 and 1,440 observations respectively. Table 5 (columns 5–6) reveals that digital transformation exerts a statistically meaningful positive impact within high-competition sectors. Notably, a one-point rise in the digitalization index corresponds to a 0.014 increase in total factor productivity (TFP), underscoring its measurable impact on operational efficiency. In contrast, the coefficient remains insignificant in low-competition industries. This indicates that digital transformation yields more pronounced TFP improvements in high-competition sectors compared to low-competition counterparts. The underlying mechanism may involve intensified competitive pressures driving enterprises to adopt information technologies for business model innovation and decision-making optimization (Melville, N., et al., 2007), thereby sustaining competitive advantages through technological advancements. Leading firms maintain or expand their leadership positions via digital transformation, while followers actively pursue similar upgrades to enhance competitiveness and overall efficiency. Conversely, low-competition and monopolistic industries exhibit higher concentration levels with rigid supply chains and stable returns, resulting in weaker incentives for digital transformation. Consequently, high-competition industries demonstrate more significant productivity-enhancing effects from digitalization initiatives than their low-competition counterparts.

Table 5. Analysis of digital dimension and enterprise external characteristic heterogeneity

Variable	(1) Digital technique	(2) Digital commerce	(3) East	(4) Midwest	(5) High competition	(6) Low competition
DIGI	0.012**	0.001	0.016**	0.015*	0.014***	0.001
	(2.495)	(1.162)	(2.563)	(1.760)	(2.677)	(0.106)
Controlled variable	control	control	control	control	control	control
Individual effects	control	control	control	control	control	control
Time effect	control	control	control	control	control	control
N	7,992	7,992	5552	2,440	6,552	1,440
R^2	0.280	0.279	0.259	0.281	0.298	0.211

Note: *, **, and *** indicate that the results are significant at the 10%,5%, and 1% significance levels, respectively. The T values in parentheses are consistent with the control variables mentioned above.

Source: Authors' calculations using CSMAR data and textual mining of annual reports (SSE/SZSE A-share manufacturers).

4.2.2.3 Internal characteristic heterogeneity of enterprises

The data was divided into two groups: state-owned entities (SOEs) and non-state-owned entities (NSOs), based on ownership, with the SOEs accounting for 2,440 entries and the NSOs comprising 5,552. As depicted in columns one and two of Table 6, we found that for the NSOs, the estimated coefficient at a 5% significance level was 0.016. This suggests that for every point increase in their digitalization score, there's a corresponding 0.016-point bump in their total factor productivity. In contrast, SOEs show an estimated coefficient of 0.015 at the 10% significance level, corresponding to a 0.015 productivity gain per unit increase in their digital transformation index. This demonstrates that manufacturing enterprises with non-state ownership exhibit more pronounced effects in boosting total factor productivity through digital transformation compared to SOEs. The primary reason may be that SOEs, which are government-controlled enterprises responsible for maintaining economic stability, adhere to stricter investment criteria and adopt risk-averse decision-making patterns (Sun, Xiangxiang, and Zhou, Xiaoliang, 2018). Conversely, non-state-owned enterprises face intense market competition and resource constraints. Prioritizing profit maximization, these firms actively pursue digital innovation and optimize resource allocation to maintain competitiveness. These analyses suggest that non-state-owned enterprises demonstrate stronger motivation for digital transformation, thereby contributing significantly to productivity enhancement.

The dataset was divided into two groups: high-tech firms (n=6,176) and non-high-tech firms (n=1,816), based on their official industry classification. Table 6 (columns 3-4) reveals that high-tech enterprises exhibit a statistically significant coefficient of 0.012 ($p < 0.05$), indicating that a one-point rise in their digital transformation index corresponds to a 0.012 increase in total factor productivity. Meanwhile, non-high-tech firms displayed a marginally higher coefficient (0.016), though this result lacked statistical significance. These findings suggest that digital transformation has a greater impact on productivity in tech-savvy companies. The research argues that high-tech firms, with their innovation-centric business models, are better positioned to embrace cutting-edge digital tools. This gives them both the incentive and the means to prioritize digital upgrades, resulting in increased investment in such initiatives. What's more, their existing R&D muscle and focus on pioneering products make their digital transformation efforts pay off faster. Let's face it—going digital isn't just about flipping a switch; it demands serious technical groundwork. High-tech companies naturally have this covered, with the right mix of infrastructure and hardware to seamlessly integrate digital solutions into their operations, both internally and across their supply chains. In summary, high-tech enterprises not only serve as key players in the digital economy but also act as pioneers in digital transformation. These companies possess both the drive and the resources to implement digital upgrades, effectively integrating production operations with digital technologies. This accelerates corporate growth while amplifying the productivity-enhancing effects of digitalization across all production factors. In contrast, non-high-tech enterprises generally exhibit weaker innovation dependency and demonstrate less urgency and focus on digital transformation compared to their high-tech counterparts.

Enterprises are categorized into two types based on whether their chairman and CEO hold concurrent positions: dual-role enterprises (n=3,864) and non-dual-role enterprises (n=4,128). As evident in Table 6 (columns 5 and 6), the digital transformation coefficient for dual-role firms remains strongly positive regardless of their degree of organizational independence. Every one-point rise in the digital transformation score corresponds to a 0.026 boost in total factor productivity for these enterprises. Meanwhile, non-dual-role businesses show a negligible impact, with an insignificant coefficient of -0.002. These findings clearly demonstrate that digital transformation drives substantially greater productivity gains in dual-role enterprises than in their conventional counterparts. The corporate governance structure reflects managerial autonomy, where the concurrent roles of chairman and CEO reduce executive constraints and enable discretionary decision-making (Crossland0 et al, 2007) This facilitates enterprises in adapting to environmental changes, formulating timely development strategies, seizing transformation opportunities, while also enhancing internal control capabilities and operational efficiency. Conversely, executives in dual-role enterprises possess higher organizational decision-making authority, which helps overcome organizational inertia, mitigate information asymmetry, and accelerate digital transformation to boost competitiveness.

Table 6. Analysis of internal characteristic heterogeneity of enterprises

Variable	(1) Belong to the state	(2) Non-state-owned	(3) High and new	(4) Not high-tech	(5) Hold a concurrent post	(6) Non-remunerative
DIGI	0.015*	0.016**	0.012**	0.016	0.026***	-0.002
	(1.760)	(2.563)	(2.219)	(1.364)	(3.661)	(-0.251)
Controlled variable	control	control	control	control	control	control
Individual effects	control	control	control	control	control	control
Time effect	control	control	control	control	control	control
N	2,440	5552	6,176	1,816	3,864	4,128
R^2	0.282	0.259	0.280	0.288	0.263	0.306

Note: *, **, and *** indicate that the results are significant at the 10%,5%, and 1% significance levels, respectively. The T values in parentheses are consistent with the control variables mentioned above.

Source: Authors' calculations using CSMAR data and textual mining of annual reports (SSE/SZSE A-share manufacturers).

4.2.3 Robustness test

To assess the reliability of our benchmark regression findings, this study performs robustness checks examining the link between digital transformation and total factor productivity through three approaches: alternative dependent variable specification, substitution of the key explanatory variable, and model specification adjustments.

The Olley-Pakes (OP) methodology effectively mitigates endogeneity concerns and sample selection biases while minimizing measurement errors, rendering it ideal for our dependent variable substitution. Following Song Min et al.(2021)'s framework, we utilize the OP method to compute total factor productivity (TFP) as a replacement for our initial dependent variable. The results, presented in Column (1) of Table 7, confirm that digital transformation exerts a statistically significant positive impact on TFP, reinforcing the robustness of our findings.

For the core explanatory variable replacement, we consider that some firms pursue digital transformation solely through business model innovation rather than investing in foundational digital infrastructure. However, true digital transformation fundamentally relies on technological advancement, with business model innovation being just one facet of a broader digital strategy. To capture this distinction, we construct a binary indicator (DIGI0-1), assigning a value of 1 to firms whose annual reports reference both digital technology adoption and business model innovation, and 0 otherwise. As evidenced in Column (2) of Table 7, the results remain consistent—digital transformation continues to boost TFP significantly, further validating our conclusions.

Finally, we refine our model specification to account for potential biases stemming from industry and regional heterogeneity. In addition to controlling for firm and time fixed effects, we incorporate industry and province fixed effects. The outcomes, displayed in Column (3) of Table 7, reaffirm that digital transformation positively and significantly enhances firm-level TFP, underscoring the stability of our empirical results across alternative specifications.

Table 7. Robustness test of the impact of digital transformation on total factor productivity

Variable	(1) TFP_{OP}	(2) TFP_{LP}	(3) TFP_{LP}
DIGI	0.012**	0.018*	0.012**
$DIGI_{0-1}$	(2.505)	(1.734)	(2.495)
Controlled variable	control	control	control
Individual effects	control	control	control
Time effect	control	control	control
Industry effects	Not controlled	Not controlled	control
Provincial effect	Not controlled	Not controlled	control
N	7,992	7,992	7992
R^2	0.278	0.280	0.280

Note: *, **, and *** indicate that the results are significant at the 10%,5%, and 1% significance levels, respectively. The T values in parentheses are consistent with the control variables mentioned above.

Source: Authors' calculations using CSMAR data and textual mining of annual reports (SSE/SZSE A-share manufacturers).

4.2.4 Endogeneity test

To address potential endogeneity concerns—including sample self-selection, reverse causality, and omitted variable bias—this study employs propensity score matching (PSM), reverse causality testing, and instrumental variable (IV) methods to mitigate these effects and validate the robustness of our findings.

(1) Propensity Score Matching (PSM) Approach. Digital transformation plays a pivotal role in corporate development, yet firms at different growth stages may exhibit selective adoption based on strategic priorities, potentially skewing research outcomes. To account for this, we utilize PSM to assess sample selection bias. First, we classify firms into two groups: those undergoing digital transformation (coded as 1) and those that are not (coded as 0). Next, we match firms based on key covariates—equity concentration, financial leverage, firm size, firm age, and current asset turnover—while using total factor productivity (TFP) as the dependent variable. Kernel matching is then applied to identify comparable control groups. As illustrated in Table 8, the average treatment effect (ATT) for digitally transformed firms remains statistically significant at the 1% level, confirming that PSM effectively minimizes systematic differences between treated and untreated firms. Column (1) of Table 9 further demonstrates that digital transformation continues to have a positive and significant impact on TFP, even after addressing selection bias, thereby reinforcing the reliability of our conclusions.

(2) Reverse Causality Analysis. While digital transformation theoretically enhances economic efficiency and TFP, firms with stronger productivity and financial performance may also be more inclined to pursue such initiatives due to their resource-intensive nature. This raises concerns about bidirectional causality. To examine this, we conduct lagged regression analysis. Results in Columns (2) and (3) of Table 9 reveal that digital transformation's productivity gains exhibit a short-term lag in manufacturing sectors, though this effect diminishes over time. This suggests that while reverse causality may initially play a role, the long-term relationship remains robust.

(3) Instrumental Variable (IV) Estimation. Despite controlling for firm-specific, financial, and macroeconomic factors, omitted variable bias remains a concern. Following Li Qi et al. (2021), we employ local government expenditure on science and technology (S&T) as an instrumental variable. This metric satisfies the relevance condition, as public S&T funding fosters regional innovation ecosystems that attract talent and R&D investments, which

indirectly incentivize corporate digital transformation (Shang Guan Xuming and Ge Bin Hua, 2020). At the same time, it meets the exclusion restriction, since such expenditures primarily target public-sector initiatives rather than directly influencing firm-level productivity.Using two-stage least squares (2SLS) regression, we obtain a first-stage F-statistic of 163.33, which is well above the critical threshold of 10, thereby ruling out concerns about weak instruments. Column (4) of Table 9 confirms that digital transformation retains a statistically significant (1% level) positive effect on TFP after IV adjustment, with results aligning closely with baseline estimates. This consistency underscores the robustness of our findings.

Table 8. Propensity score matching results

Dependent variable	Sample book	Processing group	Control group	The difference in values	Standard error	T price
TFP_{LP}	Unmatched	14.051312	13.9821267	.079800177	.007250797	11.01
	ATT	14.049301	13.9829135	.066386866	.013142522	5.05

Source: Authors' calculations using CSMAR data and textual mining of annual reports (SSE/SZSE A-share manufacturers).

Table 9. Endogeneity test of the impact of digital transformation on total factor productivity

Variable	(1) PSM	(2) One episode behind schedule	(3) Lagging behind the second phase	(4) IV-2SLS
DIGI	0.012**	0.009*	0.007	0.015***
	(2.477)	(1.754)	(1.325)	(2.654)
Controlled variable	control	control	control	control
Individual effects	control	control	control	control
Time effect	control	control	control	control
N	7,979	6,993	5,994	7992
R^2	0.280	0.293	0.319	0.277

Note: *, **, and *** indicate that the results are significant at the 10%,5%, and 1% significance levels, respectively. The T values in parentheses are consistent with the control variables mentioned above.

Source: Authors' calculations using CSMAR data and textual mining of annual reports (SSE/SZSE A-share manufacturers).

4.3 Testing the impact mechanism of digital transformation on total factor productivity

This section utilizes a mediation analysis framework to investigate the underlying mechanisms at play. To assess the innovation-driven pathway, the natural log of patent counts (IP) functions as the intermediary variable. When exploring the human capital channel, the percentage of workers holding at least a bachelor's degree (Human) acts as the mediating factor. The full mediation model is represented as follows:

$$TFP_{it}=a_0+a_1DIGI_{it}+\beta Controls_{it}+\varphi_i+\delta_t+\varepsilon_{it} \quad (2)$$

$$INTER_{it}=b_0+b_1DIGI_{it}+\beta Controls_{it}+\varphi_i+\delta_t+\varepsilon_{it} \quad (3)$$

$$TFP_{it}=c_0+\lambda INTER_{it}+c_1DIGI_{it}+\beta Controls_{it}+\varphi_i+\delta_t+\varepsilon_{it} \quad (4)$$

Among them, INTER represents the mediating variable.

As shown in Column (2) of Table 10, our estimations suggest that going digital really gives a boost to a company's ability to innovate – we're talking about patent numbers here. It appears that the digital economy is shaking up the process by which companies generate new ideas. On one hand, deep customer engagement in product and service development within digital ecosystems provides enterprises with real-time market insights, enabling agile iteration based on user feedback to accurately identify consumer needs. On the other hand, the Metcalfe effect in digital economies reduces marginal costs through accumulated user data, allowing companies to implement iterative R&D at lower innovation expenses while continuously refining products, services, and business models. Column (3) of Table 10 presents mediation effect tests for innovation-driven growth, showing statistically significant positive coefficients for patent quantity and maintaining significance for the overall digital transformation index, demonstrating how digitalization boosts total factor productivity through R&D. Column (5) reveals that digital transformation optimizes human capital structure, enhancing workforce quality. The analysis in Column (6) drives home the point with mediation effects, reinforcing the notion that digital transformation boosts overall productivity by enhancing the makeup of human capital. On the one hand, the shift towards digitalization has lessened the dependence on unskilled labor and simultaneously surged the need for top-tier talent in R&D, design, logistics, marketing, management consulting, and systems integration. Consequently, firms are better equipped to weave technological and intellectual components into their offerings, propelling efficiency gains forward (Yuan Fuhua et al, 2016). On the other hand, as enterprises enhance their capacity to allocate high-level human resources, cross-disciplinary exchanges among individuals with diverse expertise foster knowledge spillover effects that drive collaborative innovation. These synergies ultimately elevate total factor productivity within organizations.

Table 10. Mechanism test of the impact of digital transformation on total factor productivity

Variable	(1) TFP	(2) IP	(3) TFP	(4) TFP	(5) Human	(6) TFP
DIGI	0.2211*** (4.59)	1.2129*** (10.27)	0.1544*** (3.20)	0.2653*** (8.13)	15.1329*** (24.41)	0.1674*** (5.04)
IP			0.0550*** (9.79)			
Human						0.0065*** (13.23)
Other variables	control	control	control	control	control	control
Observed value	7992	7992	7992	7992	7992	7992
R^2	0.720	0.364	0.725	0.674	0.433	0.679

Note: *, **, and *** indicate that the results are significant at the 10%,5%, and 1% significance levels, respectively. The T values in parentheses are consistent with the control variables mentioned above.

Source: Authors' calculations using CSMAR data, CNRDS data, and textual mining of annual reports (SSE/SZSE A-share manufacturers).

5. Results and Conclusions

This study begins by examining the theoretical foundations of how digital transformation influences total factor productivity (TFP) growth in manufacturing firms. Leveraging textual analysis, it then assesses variations in digital adoption across different enterprise profiles while empirically evaluating its productivity effects. Key findings reveal: (1) Digital transformation consistently demonstrates a strong positive correlation with TFP gains in manufacturing, with results holding firm through rigorous robustness checks and endogeneity controls—confirming its status as a pivotal productivity catalyst. (2) The analysis uncovers two primary mechanisms: first, by amplifying innovation capacity (evidenced through increased patent output), and second, by upgrading workforce quality (measured by rising shares of bachelor's-degree-educated employees). By stimulating innovation vitality and upgrading human capital simultaneously, digital transformation indirectly drives TFP growth. (3) Heterogeneity analysis reveals more substantial effects from improved digital technology adoption than from digital business models. Digital transformation delivers a more substantial boost to total factor productivity (TFP) for certain types of businesses—particularly those based in eastern regions, operating in competitive markets, or belonging to the private sector. The impact is especially noticeable among tech-driven companies and firms that serve multiple business functions. This aligns with the earlier textual analysis, indicating these groups exhibit higher digital transformation levels, highlighting differentiated performance across dimensions, external environments, and internal characteristics. Accordingly, this work suggests these policy directives:

Initially, businesses must make digital advancement a key catalyst for boosting overall productivity, with a focus on broader implementation of digital solutions. They need to increase investment in AI, industrial internet, and Manufacturing Execution Systems (MES), driving digital upgrades across R&D, production, and logistics processes. By leveraging technological integration, companies can optimize workflows and reduce transaction costs. Simultaneously, they should strengthen innovation capabilities through big data analytics to capture market demands, facilitate customer-driven innovation and rapid iterative development, thereby improving patent quality and commercialization efficiency. Additionally, proactive optimization of human capital structure is essential—this includes recruiting highly educated technical professionals and conducting digital skills training—to provide talent support for digital transformation.

Second, to facilitate corporate digital transformation, the government should foster an enabling environment through structural reforms. With central and western regions facing inadequate digital infrastructure, targeted investments in cutting-edge technologies—such as 5G deployment and industrial internet platforms—are essential to level the playing field across different areas. For low-competition industries, policy guidance should strengthen market competition mechanisms to encourage enterprises to advance digital transformation proactively. Meanwhile, the innovation support system should be enhanced by increasing subsidies for digital R&D in manufacturing enterprises, as well as encouraging collaboration between businesses and universities/research institutions to develop digital technology innovation platforms, thereby accelerating the commercialization of technological achievements.

Third, China's economy has evolved from breakneck expansion to a focus on sustainable, high-caliber growth—shifting gears from old-school factor-driven models to cutting-edge innovation as its primary engine. As the digital economy merges with traditional manufacturing, fostering multifaceted innovation becomes the linchpin for propelling businesses into the digital age. Enterprises should develop differentiated strategies based on their unique characteristics. Non-state-owned enterprises can accelerate transformation through flexible decision-making, while state-owned enterprises need to break organizational inertia by establishing market-oriented incentive mechanisms. At the same time, high-tech companies should leverage their technological advantages to create a dual-drive model that combines "digitalization + innovation.” Simultaneously, traditional business processes should be comprehensively upgraded using new digital technologies, while adopting internet-based thinking for organizational and institutional innovations. This approach will continuously stimulate internal innovation vitality and propel high-quality development in manufacturing.

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