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Impact of Firm Ownership on Manufacturing Performance through Digital Transformation

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Abstract
As information technology continues to advance rapidly, digital transformation has become a pivotal trend for enhancing productivity and competitiveness in manufacturing enterprises worldwide. This study investigates the influence of digital transformation on production efficiency among Chinese listed manufacturing firms from 2011 to 2021. To analyze this relationship, we employ a dynamic common factor model combined with a panel data quantile regression approach, allowing for the assessment of efficiency effects across different performance levels. The results reveal a path-dependent pattern: at lower levels of production efficiency, the benefits of digital transformation are modest, whereas once a critical efficiency threshold is exceeded, its positive impact on productivity becomes substantially more pronounced. Additionally, the study demonstrates that the effects of digital transformation vary across ownership types. High-tech state-owned and private firms gain significant advantages in cost reduction, innovation, alleviation of financial constraints, and improvements in both decision-making processes and human capital. In contrast, non-high-tech state-owned firms show limited gains in cost efficiency and decision-making, while non-high-tech private enterprises experience minimal productivity benefits from human capital development. These findings underscore the importance of aligning digital transformation initiatives with firm ownership characteristics. By highlighting the heterogeneous outcomes of digital transformation, this research offers actionable insights for managers and policymakers seeking to maximize efficiency gains and strategic value through technology adoption in the manufacturing sector.

Keywords: Digital Transformation; Manufacturing; Productivity; Enterprise Ownership

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1. Introduction

The introduction of Industry 4.0 by Germany in 2011 initiated a global push toward manufacturing digitalisation. Germany's "Digital Strategy 2025" sought to strengthen national competitiveness and promote industrial modernisation by focusing on digital infrastructure, data utilisation, and industrial digital transformation. The COVID-19 pandemic further highlighted the urgency of digital adoption, as manufacturing firms confronted organisational challenges, disrupted capital chains, and declining demand. Increasingly, traditional companies are leveraging digital technologies and workforce improvements to enhance resilience and crisis response. According to Twilio's COVID-19 Digital Engagement Report, senior executives widely acknowledge the pandemic as a catalyst for accelerated digital transformation. Digitalisation enables firms to optimise production organisation (Brynjolfsson & Hitt, 2000), redefine internal and external boundaries (Plekhanov et al., 2023), establish intelligent service systems (Beverungen et al., 2019), and stimulate business growth (Magni et al., 2022). Nevertheless, hesitation remains due to concerns over operational disruption and ROI delays (Parviainen et al., 2017; Jones et al., 2021). Large firms have created digital divisions but encounter challenges like limited digital expertise, organisational complexity, and insufficient employee literacy. Digital transformation integrates IT with structural and organisational changes to generate value in products and services (Chanias et al., 2019; Gurbaxani & Dunkle, 2019; Vial, 2021; Hinings et al., 2018), focusing on three aspects: improving production methods, enhancing organisational strategies and capabilities, and driving market-wide innovation. Existing studies reveal mixed findings on its effect on productivity, especially when considering ownership differences (Caggese & Cunat, 2013; Watanabe et al., 2018; Karhade & Dong, 2021). This study addresses these gaps by evaluating digital transformation's effects on manufacturing productivity through cost reduction, innovation, alleviating financing constraints, decision-making efficiency, and human capital optimisation, while exploring heterogeneity across property rights using a dynamic common factor model.

2. Literature Review and Hypothesis Development

According to the Resource-Based View, a firm's unique and high-quality resources are fundamental sources of competitive advantage and profitability (Wernerfelt, 1984; Barney, 1999). Differences in ownership influence how firms apply digital transformation to enhance productivity. Private firms may benefit from flexibility in market adaptation, whereas state-owned firms rely on institutional advantages but face regulatory and social obligations. Therefore, digital transformation's effects on productivity are expected to vary across ownership types, giving rise to Hypothesis 1:

H1. *The productivity effects of digital transformation differ depending on ownership.*

Digital technologies allow firms to integrate supply, production, marketing, and customer functions, restructuring organisational processes for more intelligent and lean operations. Automated monitoring, improved information flow, and networked structures reduce labour dependency, cut costs, and facilitate collaboration across departments (Shinkarenko et al., 2020; Pershina et al., 2019), supporting Hypothesis 2:

H2. *Digital transformation increases productivity by lowering costs.*

Innovation is a key driver of sustainable competitive advantage. Digital transformation fosters enterprise-wide innovation, promotes collaborative innovation with stakeholders, and enhances operational efficiency (Appio et al., 2021; Nambisan et al., 2019), leading to Hypothesis 3:

H3. *Productivity improves through enhanced innovation capabilities.*

Financial constraints often limit firms' ability to invest in production and R&D, particularly in China (Li et al., 2022). By enhancing transparency and access to financing, digital transformation mitigates these limitations, facilitating resource allocation and strategic investments (Ho et al., 2023), resulting in Hypothesis 4:

H4. *Productivity rises as financing constraints are alleviated.*

Furthermore, digitalisation reduces information asymmetry, improving decision-making and supervisory effectiveness (Aben et al., 2021; Loebbecke & Picot, 2015; To et al., 2018), supporting Hypothesis 5:

H5. *Digital transformation enhances productivity via governance efficiency.*

Finally, digital tools optimise human capital by fostering technological skills, knowledge spillovers, and innovation adoption, further increasing production efficiency (Brynjolfsson & Hitt, 2003; Fleisher et al., 2010), leading to Hypothesis 6:

H6. *Digital transformation strengthens productivity through improved human capital.*

By integrating data as a vital production factor, digital transformation facilitates real-time decision-making, cross-functional collaboration, and better resource allocation (Meng & Wang, 2023; Chen et al., 2021; Wang & Shao, 2024). While challenges such as the "IT Productivity Paradox" exist (Acemoglu et al., 2014; Lin & Shao, 2006), the overall impact of digital transformation on manufacturing productivity is expected to be positive, moderated by firm ownership characteristics.

3. Research Methods

3.1. Model setting and cross-sectional correlation test

To examine the effect of enterprise digital transformation on production efficiency, this study defines the model with the following variables. The dependent variable is the firm's total factor productivity (TFP), measured using the Levinsohn-Petrin (LP) method (Levinsohn & Petrin, 2003). Total output is proxied by the logarithm of operating income, while capital investment is measured by the logarithm of net fixed assets. Intermediate inputs include the logarithm of operating, selling, administrative, and financial expenses minus depreciation and amortisation, plus employee compensation.

The primary explanatory variable is the degree of digital transformation (DT). Text analysis was employed to construct this variable by extracting annual reports of all A-share listed companies on the Shanghai and Shenzhen Stock Exchanges using Python and Java PDFbox. Feature words were identified from successful digital transformation cases, followed by word segmentation and frequency analysis. High-frequency terms, supplemented by keywords from prior literature, formed the final dictionary, excluding negations (e.g., "no", "none", "not"). DT was operationalised through three core elements: fundamental digital technology, digital production techniques, and business model transformation (Ciulli & Kolk, 2019; Li et al., 2018; Park et al., 2015). A second-level measurement (DT2) incorporated additional keyword dictionaries following Hu et al. (2023).

Control variables were selected based on previous research (Cheng et al., 2023; Guom et al., 2023; Llopis-Albert et al., 2021), including R&D intensity (RD, R&D expenditure divided by operating income), firm size (Size, logarithm of total assets), firm age (Age, current year minus establishment year), profitability (Income, return on net assets), and operational efficiency (Turnover, total asset turnover).

The dataset covers industrial firms from 2011 to 2021, sourced from the Wind database and company annual reports. Sample cleaning involved three steps: removing Special Treatment (ST) firms, imputing missing values (mean imputation for <10% missing, multiple imputation for higher missing rates), and tail-trimming continuous variables at 1% and 99% to address outliers. The final panel includes 1,049 firms over 11 years. Table 2 presents descriptive statistics for all variables.

Tabel 1. Framework for measuring digital transformation in manufacturing and keyword selection

Dimensions	Classification Words	Text Combination
Digital technology application	AI	Artificial intelligence, business intelligence, image understanding, investment decision-making and support systems, intelligent data analysis, intelligent robots, machine learning, deep learning, semantic search, biometric technology, face recognition technology, speech recognition, identity authentication, autonomous driving, natural language processing
	Blockchain	Blockchain, digital currency, distributed computing, differential privacy technology, smart financial contracts
	Cloud computing	Cloud computing, stream computing, graph computing, in-memory computing, multi-party secure computing, converged architecture, billion-level development, EB storage, Internet of Things, cyber-physical systems
	Big Data	Big data, data mining, text mining, data visualization, heterogeneous data, credit reporting, billion-level development, EB-level storage, Internet of Things, cyber physical systems
Digital production mode	Smart manufacturing	Intelligence, automatic numerical control, integration, aggregation
	Intelligent control	Intelligent terminal, intelligent mobility, intelligent management, intelligent factory, intelligent logistics, intelligent warehousing, intelligent equipment, intelligent production, intelligent networking, intelligent system, intelligence, automatic control, CNC, integration, aggregation, integrated control
Business model transformation	Internet, e-commerce	Mobile Internet, Industrial Internet, Business Internet, Internet business model, Internet technology, Internet solution, Internet thinking, Internet action, Internet marketing, Internet strategy, Internet platform, Internet model, Internet ecology, e-commerce, e-business, Internet, "Internet +", online and offline, online to offline, O2O, B2B, C2C, B2C, C2B

Source: Compiled by the author (2025) based on literature review and keyword analysis of digital transformation in manufacturing.

3.2. Setting and estimation of cross-sectional correlation panel models

In micro-panel econometrics, the issue of cross-sectional dependence is critical, as neglecting it can distort estimation and lead to misleading empirical results (Sarafidis et al., 2009). Since this study uses data from manufacturing firms with similar industry characteristics, a considerable degree of interdependence across firms is expected. Ignoring such dependence may bias the estimated impact of digital transformation on productivity.

Recent advances in panel data econometrics highlight models that explicitly account for cross-sectional dependence (Hsiao, 2018). Among these, Factor-Augmented Panel Data Regression Models are widely applied, as they capture unobserved common shocks and interdependencies. Methods such as the Common Correlated Effect (CCE) approach (Pesaran, 2006), the Iterated Principal Component (IPC) method (Bai, 2009), and likelihood-based techniques have been developed within this framework. Building on these, the present study adopts the dynamic common factor model of Chudik and Pesaran (2015) to estimate the effect of digital transformation on firm-level total factor productivity (TFP), thereby reducing potential biases from cross-sectional dependence.

The empirical model is specified as:

$$\mathrm{TFP}_{it} = \alpha_i + \gamma\,\mathrm{TFP}_{it-1} + \beta_1\,\mathrm{DT1}_{it} + \beta_2\,\mathrm{DT2}_{it} + \beta_3\,\mathrm{RD}_{it} + \beta_4\,\mathrm{Size}_{it} + \beta_5\,\mathrm{Age}_{it} + \beta_6\,\mathrm{Income}_{it} + \beta_7\,\mathrm{Turnover}_{it} + \gamma T_{ift} + \varepsilon_{it} \quad (1)$$

where TFPit denotes the total factor productivity of firm iii at time ttt, αi\alpha_iαi is the individual effect, TFPit−1 is the lagged productivity, DT1it and DT2it represent digital transformation indicators, RDit is the research and development intensity, SizeitSize_{it}Sizeit is firm size, AgeitAge_{it}Ageit is firm age, IncomeitIncome_{it}Incomeit is income, Turnoverit is turnover, tγift captures time effects, and εit is the error term.

The analysis uses panel data of 1,049 firms between 2011–2021, with coefficients estimated through the CCE method. Firms are categorised by ownership (state-owned vs. private) and technology intensity (high-tech vs. non-high-tech) to capture heterogeneity in the productivity effects of digital transformation. The classification of high-tech firms follows the National Economic Industry Classification (GB/T 4754-2017) and an R&D intensity threshold (R&D expenditure ≥ 3% of revenue). Data sources include corporate annual reports and the Wind database. Sub-sample estimations were then performed.

4. Discussion

Tables 3 and 4 show that both DT1 and DT2 positively and significantly enhance productivity, with DT2 exerting a stronger effect. Lagged productivity also has a significant positive effect, confirming dynamic persistence. Sub-sample analysis indicates heterogeneous impacts: high-tech SOEs gain the largest efficiency improvements from digital transformation, while in non-high-tech sectors, private firms outperform SOEs. These patterns reflect differences in resource availability, innovation capability, and organisational adaptability, where SOEs benefit from political and resource support in high-tech industries, whereas private firms show greater flexibility and competitiveness in traditional, less knowledge-intensive sectors.

Tabel 2. Descriptive Statistical Analysis of Variables

Variable	Mean	Standard Deviation	Minimum Value	Maximum Value
TFP	10.4397	1.1820	5.2550	15.2291
DT1	19.2843	42.3843	0.0000	910.0000
DT2	29.4112	48.6499	0.0000	965.0000
RD	2.2543	1.7151	0.0000	19.0200
Size	22.2934	1.2195	18.9209	27.5470
Age	12.2380	6.7517	0.0000	30.0000
Income	7.0034	12.7287	-204.6132	153.9459
Turnover	0.7025	0.4592	0.0060	7.8714

Source: Author's calculation (2025).

Tabel 3. CCE Estimation of Dynamic Common Factor Model

Variable	All Sample Enterprises	High-Tech State-Owned	High-Tech Private	Non-High-Tech State-Owned	Non-High-Tech Private
TFP (−1)	0.1442 ***	0.1579 ***	0.1201 ***	0.0967 ***	0.1551 ***
DT1	0.0075 **	0.0094 ***	0.0048 *	0.0042 *	0.0116 ***
DT2	0.0472 **	0.0627 ***	0.0213 **	0.0466 **	0.0791 ***
RD	0.0115 ***	0.0163 ***	0.0122 ***	0.0196 ***	0.0206 ***
Size	0.0946 ***	0.0837 ***	0.0870 ***	0.0761 ***	0.1117 ***
Age	0.0339	0.0102	0.0113 *	0.0144	0.0242
Income	0.0103 ***	0.0091 ***	0.0193 ***	0.0125 ***	0.0178 ***
Turnover	0.3987 ***	0.4385 ***	0.2221 ***	0.3322 ***	0.4182 ***
CD Im test	0.7735	0.6792	0.4229	0.8826	0.7819
PUY Im test	0.4876	0.9803	0.3964	0.3983	0.7312
LM B	0.7818	0.9654	0.5391	0.8841	0.9841

Source: Author's calculation (2025).

Tabel 4. 2SLS Estimation and Robustness Analysis Results of the Model

Variable	Model 1	Model 2	Model 3	Model 4
TFP (−1)	0.0837 **	0.1228 ***		
DT1	0.0035 **	0.0089 **	0.0069 *	0.0058 **
DT2	0.0114 **	0.0131 ***	0.0183 **	0.0160 **
RD	0.0197 ***	0.0269 **	0.0299 ***	0.0249 ***
Size	0.0886 ***	0.0777 ***	0.0612 ***	0.0685 ***
Age	0.0125	0.0125 *	0.0164	0.0121
Income	0.0108 **	0.0232 ***	0.0333 ***	0.0460 **
Turnover	0.2389 ***	0.1975 ***	0.1565 ***	0.2471 **
CD Im test	0.4083	0.8998		
PUY Im test	0.5680	0.3797		
LM B	0.2567	0.1878		

*Note: *, *, *** *represent P < 0.1, P < 0.05, and P < 0.01, respectively. Source: Author's calculation (2025)*

4.1. Endogeneity and robustness analysis

Although the proposed empirical model integrates dynamic influences of both common factors and explanatory variables, the risk of endogeneity remains due to potential issues such as imperfect calibration, exclusion of relevant variables, or reverse causality between digital transformation and production efficiency. To address this, the study applies two-stage least squares (2SLS) estimation with instrumental variables. Two approaches are adopted in constructing instruments: first, the one-period lag of digital transformation levels 1 (DT1) and 2 (DT2) are used as instruments to predict their current values; second, following Kong et al. (2021), the average degree of digital transformation in the city where the firm operates serves as an alternative instrument. For robustness, two additional perspectives are considered. Initially, the production efficiency of firms, measured in the baseline model using the LP method, is re-estimated using the OP technique, and the outcomes are incorporated into the dynamic common factor model. In addition, the IPS approach is applied as an alternative estimation strategy for the common factor model. Results from the 2SLS estimations and the robustness tests (reported in Table 4) consistently show that both DT1 and DT2 significantly and positively affect the production efficiency of manufacturing enterprises. Specifically, Model 1, which employs lagged DT1 and DT2 as instruments, and Model 2, which uses the city-level average transformation index, both indicate strong positive effects. Model 3, estimated with the

OP method, confirms these findings, while Model 4, based on the IPS technique, reinforces the conclusion that digital transformation plays a key role in improving productivity. Furthermore, residual diagnostics using the CDlm, PUYlm, and LMBC tests validate the effectiveness of incorporating common factors, as they mitigate cross-sectional dependence in the model. Collectively, these results demonstrate the robustness and reliability of the empirical findings presented in this study.

Tabel 5. Estimation Results of Panel Data Quantile Regression Model

Variable	**Static Panel Quantile Regression Model**				**Dynamic Panel Quantile Regression Model**			
	τ = 0.2	τ = 0.4	τ = 0.6	τ = 0.8	τ = 0.2	τ = 0.4	τ = 0.6	τ = 0.8
TFP (−1)					0.1075 ***	0.1173 ***	0.1365 ***	0.1762 ***
DT1	0.0009	0.0019	0.0020 *	0.0026 ***	0.0131	0.0195	0.0372 **	0.0376 ***
DT2	0.0023	0.0024 **	0.0022 **	0.0022 ***	0.0031	0.0056 ***	0.0068 **	0.0076 ***
RD	0.0326 ***	0.0281 ***	0.0243 ***	0.0208 ***	0.0308 ***	0.0436 **	0.0465 **	0.0436 ***
Size	0.7573 ***	0.7639 ***	0.7695 ***	0.7744 ***	0.7936 ***	0.6895 ***	0.6433 **	0.6847 ***
Age	0.0009	0.0001	0.0005	0.0011	0.0004 *	0.0003	0.0003	0.0003
Income	0.0012 ***	0.0009 ***	0.0006 **	0.0003 **	0.0011 ***	0.0098 **	0.0082 ***	0.0074 **
Turnover	0.8467 ***	0.8717 ***	0.8927 ***	0.9118 ***	0.6685 ***	0.6102 **	0.7805 ***	0.6791 ***

*Note: *, *, *** *represent P < 0.1, P < 0.05, and P < 0.01, respectively. Source: Author's calculation (2025).*

4.2. Test of heterogeneity of production efficiency

This section explores the heterogeneous impact of digital transformation on the production efficiency of manufacturing firms by employing both static panel quantile regression and dynamic panel quantile regression using minimum distance estimation (MD-QR) and penalized instrumental variable methods. The results, summarized in Table 5 for the quantile levels of 0.2, 0.4, 0.6, and 0.8, reveal that the effects of digital transformation levels 1 (DT1) and 2 (DT2) are not statistically significant in the lower quantiles (0.2 and 0.4). However, in higher quantiles (0.6–0.8), the coefficients become positive and significant, indicating that digital transformation has limited effects on firms with lower efficiency but becomes increasingly important as efficiency improves. This pattern suggests that low-efficiency firms are typically in the early stages of digital adoption, where technological integration, organizational restructuring, and cultural adaptation remain incomplete, thereby restricting the potential benefits (Llopis-Albert et al., 2021; Wang et al., 2023). Conversely, firms with higher efficiency gain greater advantages as they expand their digital capabilities, enabling synergies between data, material, and capital flows, thus reducing reliance on traditional production factors and overcoming path dependence (Cavalcante et al., 2011; Doz & Kosonen, 2010). The transition from industrial to digital paradigms also requires a mindset shift in management practices (Einav & Levin, 2014), which initially faces resistance but eventually enhances efficiency as digitalisation deepens. Furthermore, the marginal effects of digital transformation amplify over time, as its ability to combine data with conventional production elements generates cost reductions, productivity gains, and long-term value creation (Gaglio et al., 2022; Yang et al., 2024).

Sub-sample analysis by ownership type confirms that both state-owned and private firms share these heterogeneous patterns, reinforcing the conclusion that the efficiency gains from digital transformation vary depending on firms' initial productivity levels and their ability to overcome path dependence.

4.3. Influence mechanism identification test

From a theoretical perspective, digital transformation enhances the operational performance of manufacturing enterprises by lowering costs, strengthening innovation capacity, easing financial constraints, improving the efficiency of decision-making and supervision, and upgrading the quality of human capital. To empirically verify these mechanisms, this study applies an interaction-term approach to identify the specific mediating pathways through which digital transformation affects productivity.

The mechanism variables employed in the analysis are as follows. Mechanism 1: Enterprise cost, measured as the ratio of total operating cost to total revenue. Mechanism 2: Innovation capacity, proxied following Thornhill (2006) by the share of revenue from new product sales relative to total revenue. Mechanism 3: Financing constraints, calculated using the KZ index developed by Hadlock and Pierce (2010). Mechanism 4: Decision-making efficiency and supervisory effectiveness, represented by the ratio of management expenses to total costs. Mechanism 5: Human capital level, captured using the method of Vinogradov and Kolvereid (2007), which relies on the average years of education among employees as an indicator of workforce quality.

To conduct the mechanism analysis, this study specifies the following dynamic common factor model:

$$TFP_{it} = \alpha_i + \gamma TFP_{it-1} + \beta_1 DT1_{it} + \beta_2 DT2_{it} + \beta_{3(DT1_{it} \times Me_{it})} + \beta_{4(DT2_{it} \times Me_{it})} + \beta_5 RD_{it} + \beta_6 Size_{it} + \beta_7 Age_{it} + \beta_8 Income_{it} + \beta_9 Turnover_{it} + \gamma T_{ift} + \varepsilon_{it} \quad (2)$$

where TFPit denotes total factor productivity of firm *i* in year *t*. DT1 and DT2DT2DT2 represent two degrees of digital transformation, Meit is the mechanism variable, while R&D intensity, firm size, age, income, and turnover serve as control variables. Year fixed effects are also included.

To capture heterogeneity across ownership structures, the sample is divided into four categories: high-tech state-owned enterprises, high-tech private enterprises, non-high-tech state-owned enterprises, and non-high-tech private enterprises. Model (4) is estimated separately for each group, and the results are summarized in Tables 6–9. Within each table, Models 1 to 5 correspond to the mediation tests for mechanism variables 1 through 5.

Table 6 reports results for high-tech state-owned enterprises. In Model 1, the coefficients on the interaction of enterprise cost with DT1 and DT2 are −0.0453 and −0.0764, respectively, both significant at the 5% level. Model 2 shows positive and significant coefficients (0.0857 for DT1 and 0.0162 for DT2) when innovation capability is introduced. In Model 3, financing constraints yield significant negative coefficients (−0.0470 for DT1 and −0.0646 for DT2). Model 4 also confirms significant interactions for decision-making efficiency and supervisory effectiveness, while Model 5 demonstrates that human capital positively mediates the effect of digital transformation, with coefficients of 0.0903 (DT1) and 0.0272 (DT2). These findings are consistent with the earlier theoretical mechanism analysis.

In contrast, non-high-tech state-owned enterprises (Table 7) exhibit insignificant results for cost reduction and decision-making efficiency. For instance, the interaction coefficients in Model 1 are 0.0008 (DT1) and 0.0059 (DT2), both insignificant, while in Model 4 the coefficients (0.0088 and 0.0013) also lack significance. This divergence can be attributed to agency problems, which are more pronounced in state-owned firms (Zhang, 1997). Such problems raise transaction costs and reduce managerial efficiency, preventing digital transformation from delivering productivity gains through cost control or improved supervision. Furthermore, state-owned firms often face misaligned objectives between managers and shareholders, as performance assessments incorporate not only economic growth but also social responsibilities. Bureaucratic constraints such as the "Three Importants and One Large" decision-making system—further slow down managerial responses. Therefore, enhancing cost control and decision-making efficiency should be prioritized by non-high-tech state-owned enterprises to fully leverage digital transformation.

Table 8 shows results for high-tech private firms. In Model 1, cost-related coefficients are negative and significant (−0.0012 for DT1 and −0.0077 for DT2 at the 1% level). Model 2 reports significant positive coefficients for innovation capability (0.0031 and 0.0097). Financing constraints in Model 3 also exhibit significant negative effects (−0.0025 and −0.0039). Model 4 indicates significant negative coefficients (−0.0078 and −0.0086) for decision-making and supervisory effectiveness, while Model 5 highlights significant positive mediation through human capital (0.0012 for DT1 and 0.0048 for DT2). These findings confirm that high-tech private enterprises can effectively channel digital transformation into productivity improvements through multiple pathways.

Finally, Table 9 presents results for non-high-tech private firms. Unlike their high-tech counterparts, the interaction coefficients between human capital and digital transformation (0.0074 and 0.0092) are not statistically significant. This implies that digital transformation alone is insufficient without complementary structural and human resource adjustments. True productivity gains require integrating digital technologies with stronger human capital support. Digitalization tends to substitute low-skilled labor with technical staff, making talent development crucial (Lewis & Cho, 2011). High-tech firms, being more knowledge-intensive, emphasize innovation and talent acquisition, which allows them to exploit digital transformation more effectively. Yet, for non-high-tech enterprises, the absence of adequate human capital remains a bottleneck. As Acemoglu and Zilibotti (2001) note, advanced human capital and technological capital are complementary, and their combination enhances efficiency. Without sufficient accumulation of skilled labor, non-high-tech firms struggle to fully capture the productivity benefits of digital transformation. Thus, for these firms, the key challenge lies in building and accumulating human capital rather than merely upgrading it.

Tabel 6. Estimation Results of the Dynamic Common Factor Model of the Impact Mechanism of High-Tech State-Owned Enterprises

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
TFP (−1)	0.1110 ***	0.1012 ***	0.1452 ***	0.1268 ***	0.1785 **
DT1	0.0042 **	0.0054 **	0.0088 ***	0.0045 ***	0.0030 ***
DT2	0.0375 **	0.0411 ***	0.0206 **	0.0331 ***	0.0422 ***
DT1 × Me	−0.0453 **	0.0857 **	−0.0470 **	−0.0694 ***	0.0903 ***
DT2 × Me	−0.0764 **	0.0162 ***	−0.0646 ***	−0.0615 ***	0.0272 ***
RD	0.0108 ***	0.0929 ***	0.0758 **	0.0067 **	0.0585 **
Size	0.0307 ***	0.0865 **	0.0238 ***	0.0761 ***	0.0216 ***
Age	0.0022	0.0079	0.0034	0.0081	0.0089
Income	0.0312 ***	0.0465 ***	0.0591 **	0.0552 **	0.0216 ***
Turnover	0.5519 ***	0.8223 ***	0.1819 ***	0.1191 ***	0.6990 ***
CD lm test	0.8023	0.7674	0.3764	0.5564	0.4533
PUY lm test	0.8067	0.1522	0.3784	0.1084	0.2331

LM B	0.1945	0.1758	0.3438	0.9585	0.9127

*Note: *, *, *** represent P < 0.1, P < 0.05, and P < 0.01, respectively. Source: Author's calculation (2025).

Tabel 7. Estimation Results of the Dynamic Common Factor Model of the Impact Mechanism of Non-High-Tech State-Owned Enterprises

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
TFP (–1)	0.1312 ***	0.1642 ***	0.1780 ***	0.1707 ***	0.1762 ***
DT1	0.0025 ***	0.0023 **	0.0057 ***	0.0037 ***	0.0061 ***
DT2	0.0361 ***	0.0140 **	0.0423 ***	0.0804 **	0.0124 **
DT1 × Me	0.0008	0.0281 ***	–0.0924 ***	0.0088	0.0911 ***
DT2 × Me	0.0059	0.0070 ***	–0.0541 ***	0.0013	0.0546 ***
RD	0.0505 **	0.9729 ***	0.2943 **	0.7459 ***	0.2357 ***
Size	0.0664 ***	0.0172 **	0.0634 **	0.0070 ***	0.0135 ***
Age	0.0022	0.7555	0.7411	0.6514	0.9590
Income	0.0220 **	0.0865 ***	0.0427 ***	0.3343 ***	0.5554 *
Turnover	0.3562 **	0.3303 ***	0.3135 **	0.1191 ***	0.6990 ***
CD lm test	0.7952	0.3139	0.6864	0.1424	0.6574
PUY lm test	0.5511	0.6930	0.3266	0.9814	0.2871
LM B	0.3212	0.5921	0.1339	0.7163	0.1386

*Note: *, *, *** represent P < 0.1, P < 0.05, and P < 0.01, respectively. Source: Author's calculation (2025).

Tabel 8. Estimation Results of the Dynamic Common Factor Model of the Impact Mechanism of High-Tech Private Enterprises

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
TFP (–1)	0.1359 **	0.1071 **	0.1829 ***	0.1555 ***	0.1559 ***
DT1	0.0082 **	0.0067 **	0.0023 ***	0.0045 ***	0.0087 ***
DT2	0.0946 **	0.0382 **	0.0429 ***	0.0137 ***	0.0774 ***
DT1 × Me	–0.0012 ***	0.0031 ***	–0.0025 ***	–0.0078 **	0.0012 **
DT2 × Me	–0.0077 ***	0.0097 ***	–0.0039 ***	–0.0086 **	0.0048 ***
RD	0.0168 ***	0.0393 **	0.0009 **	0.0407 ***	0.0552 ***
Size	0.0676 ***	0.0433 **	0.0554 ***	0.0200 ***	0.0025 *
Age	0.0074	0.0098	0.0055	0.0095	0.0097
Income	0.0232 ***	0.0903 ***	0.0216 **	0.0157 **	0.0662 **
Turnover	0.3828 ***	0.1888 **	0.2398 ***	0.6896 **	0.6162 **
CD lm test	0.5959	0.2871	0.5402	0.5924	0.6991
PUY lm test	0.6955	0.1532	0.6030	0.2957	0.4059
LM B	0.9877	0.9941	0.8829	0.4456	0.8032

*Note: *, *, *** represent P < 0.1, P < 0.05, and P < 0.01, respectively. Source: Author's calculation (2025).

Tabel 9. Estimation results of the dynamic common factor model of the impact mechanism of non-high-tech private enterprises

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
TFP (–1)	0.1672 ***	0.1078 ***	0.1175 ***	0.1829 ***	0.1080 ***
DT1	0.0022 ***	0.0005 **	0.0001 **	0.0023 ***	0.0003 **
DT2	0.0241 **	0.0906 **	0.0441 **	0.0105 ***	0.0211 **
DT1 × Me	–0.0013 ***	0.0028 **	–0.0017 **	–0.0060 **	0.0074
DT2 × Me	–0.0097 **	0.0050 **	–0.0038 **	–0.0031 **	0.0092

RD	0.0052 ***	0.0543 *	0.0580 **	0.0989 *	0.0401 ***
Size	0.0442 ***	0.0107 ***	0.0873 ***	0.0520 ***	0.0990 ***
Age	0.0086	0.0029	0.0048	0.0026	0.0053
Income	0.0588 ***	0.0697 ***	0.0345 ***	0.0684 **	0.0931 ***
Turnover	0.3671 ***	0.3655 ***	0.1137 ***	0.3285 **	0.3507 ***
CD lm test	0.6474	0.1580	0.1762	0.8954	0.9440
PUY lm test	0.5905	0.6993	0.6320	0.4944	0.1379
LM B	0.9612	0.1953	0.3547	0.2254	0.1697

*Note: *, *, *** represent P < 0.1, P < 0.05, and P < 0.01, respectively. Source: Author's calculation (2025).

5. Discussion

This study contributes theoretically to the literature on the nexus between digital transformation and productivity in manufacturing firms. First, while prior studies have rarely addressed how ownership structure shapes this relationship, the present work provides empirical evidence by distinguishing manufacturing enterprises into four groups: high-tech state-owned, high-tech private, non-high-tech state-owned, and non-high-tech private firms. This classification allows for a deeper understanding of how property rights and technological intensity moderate the impact of digital transformation. The results demonstrate that for technologically advanced firms, digital transformation exerts a stronger influence on productivity in state-owned enterprises, whereas in less technologically developed firms, private enterprises benefit more prominently. These findings enrich the theoretical discourse on the role of digital transformation in productivity enhancement.

The research advances theory by analyzing heterogeneity in digital transformation's effects through a quantile regression approach applied to panel data. The evidence shows that the benefits of digital transformation are limited for firms at the lower end of the productivity distribution, but become increasingly significant as production efficiency rises. This pattern is further interpreted through the lenses of cognitive orientation and marginal benefits, offering a novel theoretical perspective for assessing how digital transformation interacts with varying levels of firm performance.

Beyond examining the direct link between digital transformation and productivity, this study also explores the underlying mechanisms differentiated by ownership type. Specifically, the analysis highlights how digital transformation can reduce operational costs, stimulate innovation, ease financing constraints, improve decision-making and supervisory efficiency, and strengthen human capital structures. By identifying these critical "pain points," the study presents a systematic framework to explain how digital transformation contributes to productivity growth in manufacturing enterprises.

Digital transformation has become deeply embedded in modern life and is increasingly recognized as a matter of global concern (Demiryurek et al., 2020). This study sheds light on how its influence on the efficiency of manufacturing firms varies according to ownership structure and, based on these insights, proposes several managerial implications.

First, firms should design tailored digital transformation strategies that align with the strengths and weaknesses of different ownership types, ensuring that resources are allocated effectively to maximize efficiency gains. For instance, high-tech state-owned enterprises can leverage their abundant resources and implicit government support to advance digital initiatives. By doing so, they may achieve cost reductions, foster innovation, and enhance decision-making processes, which together strengthen productivity. On the other hand, low-tech private enterprises can take advantage of their greater flexibility and organizational agility, enabling them to adapt and upgrade more rapidly in order to capture the productivity benefits of digital transformation. Customized approaches allow firms across ownership categories to pursue development paths suited to their contexts and secure sustained growth and competitiveness.

Second, analyzing the specific channels through which digital transformation affects productivity not only deepens managers' understanding of the link between digital adoption and firm performance, but also provides actionable recommendations. Firms should aim to clearly identify and strategically utilize the transformation pathways most relevant to them—whether that involves tackling agency conflicts, reducing bureaucratic inefficiencies, improving decision-making, or building stronger human capital bases. Addressing these issues systematically will enable firms to better realize the dividends of digital transformation.

Third, companies should adopt differentiated approaches to implementing digital transformation depending on their stage of development. The process is complex and requires careful planning, especially given the uncertainties associated with rapid technological change (Warner & Wäger, 2019). As external conditions evolve, firms actively pursue opportunities to digitalize (Chen et al., 2024), but the sequencing matters. During the early stages of growth, priority should be placed on building human capital, maintaining organizational flexibility, and timing the transition beyond traditional manufacturing practices carefully. As firms mature, however, they must be prepared to embrace digital transformation more boldly, breaking dependence on outdated managerial models and fully exploiting the efficiency gains offered by digital technologies.

6. Conclusions

This study focuses specifically on ownership structure as the lens for analyzing the impact of digital transformation on the production efficiency of manufacturing enterprises. Employing the panel common factor model and panel quantile regression model, data from Shanghai and Shenzhen A-share listed manufacturing firms between 2011 and 2021 were examined. The findings highlight several key insights.

Digital transformation exerts distinct effects depending on ownership type. High-tech state-owned enterprises benefit more strongly from digital initiatives compared to their non-state-owned counterparts. This advantage is largely driven by institutional support, economies of scale, and implicit government backing. In contrast, within non-high-tech sectors, state-owned firms lag behind non-state-owned enterprises, mainly due to weaker innovation capacity and reduced organizational flexibility.

The influence of digital transformation on productivity is heterogeneous across firms at different efficiency levels. For enterprises with low productivity, the improvement derived from digital initiatives remains minimal. However, once firms reach moderate or higher productivity levels, the positive impact of digital transformation becomes progressively stronger. This pattern is linked to the dynamic but path-dependent nature of digitalization, where resistance to change—rooted in longstanding institutional practices—limits firms' willingness and motivation to transform.

The mediating mechanism analysis reveals that both high-tech state-owned and private manufacturing firms can leverage digital transformation to improve efficiency through multiple channels, including cost reduction, innovation enhancement, mitigation of financing constraints, more effective decision-making, stronger supervisory capacity, and the development of human capital. Conversely, such benefits are not consistently observed in non-high-tech enterprises. For non-high-tech state-owned firms, autonomy and structural rigidity hinder efficiency gains, while in non-high-tech private enterprises, limited investment in scientific and technological innovation weakens the role of human capital improvement as a driver of productivity growth.

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