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THE EFFECT OF DIGITAL TRANSFORMATION ON MANUFACTURING ENTERPRISE PERFORMANCE

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Abstract

Recent evidence indicates that the proportion of manufacturing enterprises undergoing digital transformation and the digital investment made by manufacturing enterprises are increasing, suggesting that digital transformation may affect the production and operation of manufacturing enterprises. This paper investigates the influence of digital transformation on the performance of manufacturing enterprises and the intermediary effect of efficiency and costs. We take the annual reports of 156 listed Chinese manufacturing enterprises from 2015 to 2019 as samples for data collection and apply the textual analysis method to build the digital transformation index of manufacturing enterprises. Our analysis shows that the digital transformation of manufacturing enterprises plays a positive role in improving enterprise performance. Based on the path analysis, digital transformation indirectly improves the performance of the manufacturing enterprise by improving operational efficiency and reducing production costs. We also found that the level of digital transformation is related to the performance of Chinese manufacturing enterprises. A relatively low level of digital transformation does not have a significant impact on the performance of the Chinese manufacturing enterprise. However, medium and high levels of digital transformation will significantly increase the performance of manufacturing enterprises. Our study contributes to providing new ideas to construct enterprise digital transformation indicators. We also offer new insights into different levels of enterprise digital transformation on enterprise performance.

Keywords: Digital transformation, enterprise performance, textual analysis, manufacturing enterprise.

JEL Classification: D22, D24, L25

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Introduction

The positive effects of digital transformation on the development of the manufacturing industry have been recognised by significant manufacturing countries (Vial, 2019), many of which have developed national development plans to promote the digital transformation of the manufacturing industry. The 2016 World Economic Forum in Germany was themed “Mastering the Fourth Industrial Revolution”, acknowledging the power of digital transformation. The path of digital transformation has attracted considerable attention in all countries. China has always maintained certain advantages based on its complete industrial manufacturing chain and low overhead. Given the continuous increase in total manufacturing costs, China's competitive advantages are likely to decline. Research on digital transformation has developed in stages, from the role of digital transformation, the motivation of digital transformation, to the mode of digital transformation (Appio et al., 2021; Fossen and Sorgner, 2021). Studies related to digital transformation have achieved specific results. However, there is no consensus on the definition of digital transformation, and the effect of digital transformation on enterprise performance is rarely examined.

What is digital transformation? It can be traced back to the impact of technological development. From technological development, the concept moves to existing digital technologies such as social media, mobile devices, and embedded equipment, as well as IT, big data, cloud computing, the mobile Internet, and enterprise resource planning. It can manifest itself primarily in business improvements, such as improving customer experience, simplifying operations, or innovating new business models, digital innovation of products (Fitzgerald, 2014), and the impact on organisational structure (Li, et al., 2018). Based on existing research, we use the Wu, Lou and Hitt (2019) proposed definition as a reference and combine the perspectives of Bresciani et al. (2021). This article defines enterprise digital transformation as the leverage of big data, AI, the Internet of Things (IoT), and other advanced technologies, followed by the analysis of the data obtained to improve business efficiency and reshape and innovate the current business model.

Digital transformation has a long-term impact on organisations and society (Nambisan, Wright and Feldman, 2019). According to different research objects, digital transformation has been related to numerous fields, including health care (Agarwal et al., 2010), banking (Sia, Weill and Zhang, 2021), industry (Frank, Dalenogare and Ayala, 2019), government (Tangi et al., 2021), etc. Initial research on digital transformation focused on defining the concept, the motivations for transformation, the mode of transformation, and the stages of transformation, with the aim of providing a more comprehensive understanding and interpretation of emerging phenomena (Vial, 2019). As research has deepened, some studies have focused on constructing a digital transformation framework (Correani et al., 2020), considering digital transformation as an overall strategic framework.

With the digital transformation that penetrates various fields of production and life, the impact and consequences of this transformation on various economic entities have attracted considerable research attention. Some scholars discussed the role of digital transformation in boosting national economies, building smart cities, digital government, and enabling environmental sustainability (Konninos et al., 2021). However, digital transformation must be based on existing industrial structures and production methods, indicating that the main driver of transformation should be the real economy, particularly the manufacturing industry. Studies based on the enterprise level have clarified the effect of the internal logic of digital

transformation on enterprise production and operation activities by examining multiple dimensions, investigating aspects of enterprise production efficiency, collaborative clustering, innovation capabilities, and analysing the mechanisms of action and paths of influence (Jacobides, Cennamo and Gawer, 2018).

Previous studies have mainly considered the key elements of digital transformation and the driving forces of digital transformation (Park, Choi and Hong, 2015; Vial, 2019). There is an urgent need for the output of the digital transformation of enterprises. Therefore, this article focusses on manufacturing companies, examining the impacts of the digital transformation of manufacturing companies on performance. Furthermore, there is little research on digital transformation indicators. Previous studies have mainly used quantitative methods such as questionnaires, dummy variables, and substitution variables to develop digital transformation indicators. This study seeks to identify keywords from publicly disclosed annual reports of companies using textual analysis (Brochet et al., 2015), building enterprise digital transformation indicators.

Compared to the existing literature, the contributions of this paper are twofold. First, based on the microdata of listed companies, this paper uses textual analysis methods to construct digital transformation indicators for companies, offering a valuable supplement at the microlevel. Second, this study examines the different levels of digital transformation that impact enterprise performance.

The remainder of this paper is structured as follows: Section 1 introduces the research hypotheses. Section 2 introduces the research methodology. Section 3 reports the results. The final section presents a discussion and conclusions.

1. Hypotheses

In the rapidly advancing digital age, enterprises face the dilemma of the inability of the marginal contribution of traditional factors to maintain sustainable development, and it is urgently necessary to introduce new technologies to achieve further growth momentum. Its potential social and economic impacts are uncertain when technology is applied and promoted. Productivity can be improved through technological innovation, primarily due to efficiency improvements, or be restricted by existing production processes, resulting in higher transformation costs and reduced promotion effect.

According to competitive advantage theory, competitive advantage determines economic performance and enterprises can achieve high-quality growth by breaking internal boundaries and strategically integrating resources. With the rapid development of the digital economy, data have become an emerging production factor capable of unleashing the development potential of an enterprise. Data and traditional production factors, including capital and labour, participate in the production process, continuously seeking to expand and optimise the enterprise's system of production factors, improve resource allocation, and enhance internal competitiveness (Chen et al., 2022). Therefore, digital transformation in manufacturing enterprises is assumed to positively affect enterprise performance. Digital transformation involves big data, providing a broad space for data mining and organisational optimisation. The critical production factors driving market organisation and operations are shareable, reproducible, and reusable data and information. Circulation, diffusion, and timeliness of data and information allow iterative self-enhancement, continuously adding

new impetus for the development of enterprises and directly driving increases in productivity (Chen and Wang, 2019). When implementing digital transformation, enterprises can leverage digital technologies, including data elements and the Internet, to break through rigid sectoral barriers, promote internal specialisation division, and advance interdepartmental collaboration (Song, Dana and Berger, 2021) and finally achieve the goal of performance growth by competitive advantages (Chen et al., 2021).

The “Information Technology Productivity Paradox” argues that the digital transformation of manufacturing enterprises can have a negative impact on enterprise performance. Lin and Shao (2006) verified this paradox with empirical data. The management approach and mode of operation of an enterprise are primarily dependent on traditional production models, division of labour, and cooperation. The digital transformation of manufacturing enterprises could affect the original operating order and organisational structure of the companies, and the contradictions between the two could result in industrial rejection and a decrease in performance.

Research on the impact of digital transformation on manufacturing companies' performance, in theoretical or empirical research, remains inconclusive. Data production factors can significantly improve traditional production and operation activities and enterprise performance, but can also fall into a “technical paradox”, preventing improvement in enterprise performance. Based on the existing literature, this study proposes the following hypotheses:

H1a. The digital transformation of manufacturing enterprises has a positive effect on the growth of manufacturing enterprise performance.

H1b. The digital transformation of manufacturing enterprises has an inhibitory effect on the growth of the performance of manufacturing enterprises.

The digital transformation of enterprises can drive innovation through the application of digital technology. It can promote the transformation and remodelling of production structures and modes, resulting in overall improvements in production efficiency, capital use rates, and decision-making efficiency without changing the central core functions of the enterprise (Vial, 2019). First, digital technology can help enterprises integrate production factors and conditions, improve the automation and intelligence of production processes, and increase unit production capacities, increasing the rate of return on capital (Chen and Wang, 2019). Second, traditional production and management models focused primarily on supply and demand, performing standardised production methods. Digital transformation can help enterprises process information, strengthening the ability to acquire immediate market information and capture real-time value intelligently and digitally. This approach can effectively mitigate information asymmetry between manufacturers and consumers, breaking through the information barriers between the two central supply and demand concerns, and achieving personalised, consumer demand-orientated services. Enterprises can save considerable capital investment and improve the efficiency of capital use through the introduction of large-scale, customised lean production and operations, maximising the profitability of scarce capital and improving performance. From the perspective of strategy formulation, the upgrade of information technology has improved decision making. With the complete integration of digital technology and corporate production, management, sales and service (Llopis-Albert, Rubio and Valero, 2021), decision makers can understand the status of production and operation more accurately and comprehensively. This strengthens the

ability to effectively leverage market information through data collection, sorting, and analyses to promptly adjust strategic operational and business strategies, reducing decision-making errors, and improving decision-making efficiency, which establishes the foundation for performance growth (Chen, Wang and Chu, 2020). Therefore, the following hypothesis is proposed:

H2. The digital transformation of manufacturing enterprises increases performance by improving efficiency.

With digital transformation, enterprises can integrate the supply, production, marketing, and customer sectors, reorganising an organisational system and processes. From the perspective of production, digital transformation has effectively improved enterprise production and the digital and intelligent level of services. Enterprises can be intelligently monitored using digital technology, reducing excessive dependence on labour and saving labour costs. From an organisational perspective, under the impact and influence of digital transformation, corporate organisational structure and management models can be decentralised and focus on collaboration. New digital technology can advance the shift from management approaches toward intensive and lean models, fundamentally change the traditional means of sharing information, improve the timeliness and circulation reach of information, and promote the transformation of corporate management from vertical to flat, more networked, and platform-based. This shift can reduce management costs and improve economic efficiency (Shinkarenko, Smirnov and Beloshitskiy, 2020). Digital technology offers the possibility of a wide range of business model innovations. New industries, new business forms, and new models catalysed by new technologies allow companies to be not limited by spatial distance or physical operations, reducing maintenance cost. General changes have been identified in the value propositions, value system structures, and functional architecture of the business models. Modern technologies are interconnected with various application scenarios, providing customers with an immersive experience and strengthening and deepening the interaction and communication between enterprises and customers. With the convenience of the Internet media, companies can quickly gain insight into users' experiences and evaluations through the network platform, reducing the need for traditional marketing, and establishing the possibility of attracting and absorbing a wider market group and improving operating profit. Therefore, the following hypothesis is proposed:

H3. The digital transformation of manufacturing enterprises affects performance by controlling costs.

According to path dependence theory (North, 1981), enterprises rely on existing development paths, and traditional manufacturing is accustomed to following established production models and management systems for production and operational activities. The deep integration of digital technology represented by AI, big data, cloud computing, and blockchain with an enterprise requires financial resources and time. The existing management structure and production model of an enterprise will inhibit the effect of digital transformation. When enterprises initially prepare for digitalisation, funds are invested to introduce digital technologies (such as ICT), and the primary focus is on building a digital infrastructure. At the same time, digital technology and enterprise business integration have just begun and are not yet fully integrated. Therefore, the organisational structure and business philosophy have not yet completed the digital transformation, and the level of digitisation is low. At this stage, it is difficult to fully leverage the potential of the data elements to obtain competitiveness enhancement (Llopis-Albert, Rubio and Valero, 2021).

However, as continuous enterprise proficiency in the use of digital technology, the strengthening of the digital talent pool and the digitalisation and intelligent transformation of production and operation processes, the level of digitalisation of enterprises will continue to improve, the digital dividend will gradually emerge and expand. The influence on the performance level of enterprises will also appear. Therefore, the following hypotheses are made:

H4a. The low-level digital transformation of the enterprise does not have a significant impact on the performance of the manufacturing enterprise.

H4b. The digital transformation at the top level of the enterprise has obvious effects on the performance of the manufacturing enterprise.

2. Methodology

Based on this panel model, we examine the impact of digital transformation on manufacturing enterprise performance from multiple perspectives, empirically testing the direct and indirect effects of digital transformation on manufacturing enterprise performance using the intermediary effect model. We also use the panel threshold model to examine the impact of different levels of digital transformation on the performance of manufacturing enterprises.

2.1. Model

This study constructs panel data, intermediary effect, and panel threshold models to test the impact of digital transformation on manufacturing enterprise performance.

$$Y_{i,t} = \alpha + \zeta_1 X_{i,t} + \sum_j \nu_j \text{Control}_{j,i,t} + \xi_j + \eta_t + \varepsilon_{i,t} \tag{1}$$

Model (1) is the benchmark regression equation and the mediation effect equation, where $Y_{i,t}$ represents the performance of manufacturing enterprises, $X_{i,t}$ represents the digitalisation measurement index of manufacturing enterprises, $\text{Control}_{i,j,t}$ represents control variables, α is a constant, and ξ_j and η_t are the fixed effect of industry and time, respectively.

$$\text{Mediator}_{i,t} = \beta X_{i,t} + \xi_j + \eta_t + \varepsilon_{i,t} \tag{2}$$

$$Y_{i,t} = \tau + \theta_1 X_{i,t} + \theta_2 \text{Mediator}_{i,t} + \sum_j \theta_j + \xi_j + \eta_t + \varepsilon_{i,t} \tag{3}$$

Models (2) and (3) are mediation effect equations, among which the mediator represents the mediation variable.

$$Y_{i,t} = \epsilon + Q_1 \text{Num} * Q |D_i \leq D_1| + Q_2 \text{Num} * Q |D_1 < D_i < D_2| + Q_3 \text{Num} * Q |D_i \geq D_2| + \lambda_i X_i + \mu_i + \lambda_t + \varepsilon_{i,t} \tag{4}$$

In equation (4), this study takes the threshold digitalisation variable of a manufacturing enterprise to set the piecewise function. This study only uses the double threshold as an example to explain the constructed threshold model where is the indicator function. When the threshold condition is satisfied, it is 1; otherwise, it is 0.

2.2. Variables

The production activities of microeconomic subjects aim to maximise profit, so the economic benefits of enterprises can measure the success of digital transformation. Combined with the hypotheses proposed in this study, the explained variables include the return on total assets (ROA) and the return on net assets (ROE). The explanatory core variable is the digital transformation indicator and the control variables refer to existing research literature. The explained variables, ROA and ROE, are enterprise performance indices.

After the core explanatory variable, digital transformation, was proposed, most scholars focused on qualitative analyses, conducting research from the perspectives of meaning and definition (Nambisan, Wright and Feldman, 2019). As this research deepened, quantitative analysis was needed, and scholars tried to conduct quantitative research on digital transformation.

From the perspective of the technical implementation of the design of the digital transformation variable, the annual reports of all A-share listed enterprises on the Shanghai Stock Exchange and Shenzhen Stock Exchange were collected and sorted using the Python crawler function. The frequency of words was counted according to the characteristic words of the graph, and then from the perspectives of digital technology (Park, Choi and Hong, 2015), industrial digitisation, digitisation of business models (Ciulli and Kolk, 2019), and other information regarding digital transformation (Li, et al., 2018). Finally, we categorised and collected word frequencies in key counting directions and constructed the final sum of word frequencies, constructing an indicator system representing the digital transformation of enterprises. Given this typical type of “right-biased” characteristics, we logarithmically processed the resulting data to obtain the general indicators of digital transformation presented in Table no.1.

Table no. 1. Keywords for Digital Transformation of Manufacturing Enterprises

Digital Technology	Business Model Digitisation	Industrial Digitalisation	Other Digital Information
AI (Artificial Intelligence)	O2O	Digital Workshop	Automation
BI (Business Intelligence)	B2C	Data Channel	Platform
ERP (Enterprise Resource Planning)	B2B	New Infrastructure	Informatization
OA (Office Automation)		Intelligent Logistics	Intelligentization
Industry of Internet		Intelligent Manufacturing	Digitalisation
Internet+		Intelligent Terminal	Digital Mining
Big Data		Intelligent Plant	Data Analysis
Cloud Platform		Industry 4.0	Data Collection
Cloud computing			Database
Internet of Things			Intelligent Networking

Regarding control variables, this study uses an index to account for the primary operational conditions, capital structures, and financial circumstances of the companies, including R&D intensity, growth opportunity, firm age, and enterprise scale (limited to the length of the article, the results can be obtained from the author).

3. Results

3.1. Data

The data used in this study are from manufacturing companies listed on the main board of Shanghai and Shenzhen as the research sample, combined with the policy background of officially proposing “Made in China 2025” in 2015 (Li, 2018) and the availability of data. The research interval is set for 2015 to 2019. In this study 1,010 companies are examined, excluding companies with missing data. The enterprise annual reports are sourced from Wind databases, other financial data sources Wind, and CSMAR databases. The result presents a statistical description of the main variables of the study (limited to the length of the article, the results can be obtained from the author).

3.2. Benchmark Regression Results

Based on panel data models, this study conducts fixed-effect and random-effect regression analyses to test the impact of digital transformation of manufacturing enterprises on performance. Table no. 2 presents the results.

Table no. 2. Benchmark Regression Results

Variable	ROA		ROE	
	1	2	3	4
	Fixed Effect	Random Effect	Fixed Effect	Random Effect
Digital Transformation	0.0176*** (3.91)	0.0110*** (3.14)	0.0501*** (4.19)	0.0258*** (3.51)
Control	Yes	Yes	Yes	Yes
Constant	-0.7276*** (-3.27)	-0.1337 (-1.39)	-1.4852*** (-2.49)	-0.2846* (-3.45)
Prob>F	0.000	0.000	0.000	0.000
Prob> Chi ²	0.000	0.000	0.000	0.000
Observation	780	780	780	780
R ²	0.1707	0.1363	0.1007	0.1411
Hausman Value	Chi ² (5) = 40.87		Chi ² (5) = 25.65	
	Prob> Chi ² = 0.000		Prob> Chi ² = 0.000	

Note: Robust t-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

According to the results, regression results 1 and 3 of the panel fixed effects and the estimated coefficients of the digital transformation variable are 0.0176 and 0.0501, which meet the significance test requirement at the 1% level. They are also considered somewhat robust. The regression results 2 and 4 of the panel random effects, the estimated coefficients of the digital transformation variable are 0.0501 and 0.0258, respectively, passing the significance test at the 1% level. Overall, based on controlling relevant control variables, the digital transformation of manufacturing enterprises is positively related to enterprise performance. Therefore, H1a is supported; that is, the digital transformation of manufacturing enterprises significantly improved enterprise performance, and digital transformation is beneficial to the development of Chinese manufacturing enterprises. However, the effect could be attributed to multiple factors and paths. Only by exploring the effective way behind the improvement of enterprise performance through digital transformation can we reveal the unknowns behind the phenomena.

3.3. Endogeneity and Robustness Tests

This study selects the following instrumental variable for the estimation of least squares: the logarithm of the number of broadband ports in each province to solve possible endogenous problems. An effective instrumental variable must meet the requirements of both correlation and exogeneity. Specifically, for correlation, intelligent manufacturing is constrained by the provincial network infrastructure.

For exogeneity, it is difficult for a single enterprise to directly affect network infrastructure development. This study tests this by simultaneously adding endogenous and instrumental variables. Suppose that the regression coefficient of the instrumental variable is not significant. This indicates that the instrumental variable only affects the performance of the enterprises through the endogenous variable but does not directly affect the performance of the enterprises, which can ensure the exogeneity of an instrumental variable.

Regressions present the results based on OLS (limited by the length of the article, the results can be obtained from the author). Regression shows that the coefficient of instrumental variables is positive and not significant if there is no endogenous variable. Regression shows that after controlling for the endogenous variable, the endogenous variable digital transformation coefficient is significantly positive at the 1% level. In contrast, the instrumental variable remains insignificant, indicating that the instrumental variable affects enterprise performance only through endogenous variables. The instrumental variable will not directly affect the performance of the company, thus ensuring the exogeneity of the instrumental variables. Regressions report the regression results of the two-stage least squares (2SLS) method for the instrumental variable. The first-stage result shows that the coefficient of the instrumental variable is significant at a 1% level, indicating that the instrumental variable satisfies correlation. The results of the weak instrumental variable test show a Cragg–Donald Wald F statistic that is greater than the corresponding critical value under the 10% distortion tolerance provided by Stock and Yogo (2005), indicating that there is no weak instrumental variable problem. The result of the recognisable test shows that the LM statistic of the Anderson canonical correlation coefficient is significant at the 1% level. The result of regression shows that the transformation variable of digital transformation is significantly positive at the level of 10%, which indicates that the effect of digital transformation on the performance of the manufacturing enterprise has a promoting influence after considering endogenous problems.

To verify the robustness of the model, this study uses two different testing methods. One uses different estimation methods, selecting panel GMM estimation as a robustness test. The second is to replace the core explanatory variables with the digital transformation indicators of the enterprises, using the proportion of the aspects related to the digital economy of total intangible assets in the detailed items of intangible assets at the end of the year disclosed in the financial reports of the listed companies and the degree of change each year as proxy variables. In this study, specifically, when counting keywords related to the digital economy and technology, such as “software”, “computer software”, “software system”, “ERP system”, “cooperative office system”, “management and application software”, “financial software” and related words, detailed elements are labelled as “intangible assets: digital economy and technology”, and the various intangible assets of a company in the same year are added to calculate the proportion of intangible assets in a year; that is, the proxy variable of the digital transformation of enterprises.

The results of the regressions indicate that the coefficients of the impact of digital transformation on manufacturing enterprise performance are 0.0105 and 0.0298 and are significant at levels of 10% and 5%, respectively (limited to the length of the article, the results can be obtained from the author). The GMM estimation is used as a robustness test of the model. The results of the regressions show that the influence coefficients of the proportion of digital intangible assets on the performance of manufacturing enterprises are 0.2856 and 1.6689 and are significant at levels of 5% and 1%, respectively. The significance level and direction of the remaining control variables mirror these findings, again verifying the robustness of the model.

3.4. Mechanism Tests

According to the total effect regression analysis, the digitalisation of the manufacturing enterprise has significantly improved the enterprise performance. Considering multiple effects, it is necessary to conduct a thorough path analysis; thus, the mediation effect model is adopted (Baron and Kenny, 1986). This study uses total asset turnover and cost rates as mediation variables; that is, proxy variables for efficiency improvement and cost control routes. If the coefficient of digital transformation in model (2) and mediator (3) are significant, there is a mediation effect. The study first tests the efficiency path of enterprise digital transformation, as shown in Table no. 3.

Table no. 3. Mediation Test of Efficiency Improvement

Variable	ROA	ROE	Total Asset Turnover
	5	6	7
Digital Transformation	0.0161*** (3.59)	0.0446*** (3.77)	0.02523** (2.20)
Total Assets Turnover	0.0606*** (3.88)	0.2357*** (5.71)	
Control	Yes	Yes	Yes
Constant	-0.8489*** (-3.82)	-1.9567** (-3.34)	1.9999*** (3.54)
Time (Entity) Fixed	Yes	Yes	Yes
Observation	780	780	780
R ²	0.1905	0.1458	0.0331

Note: Robust t-statistics in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

From the results of regression 7. The coefficient in which the digital transformation of manufacturing enterprises affects total asset turnover is 0.02523, which is significant at the 5% level, indicating that the digital level of manufacturing enterprises has a significant effect on the improvement of efficiency of the enterprise. Regressions 5 and 6 are based on the benchmark regressions 1 and 3, introducing the intermediary variable total asset turnover. The benchmark regression results demonstrate that the influence of total asset turnover on enterprise performance is significantly positive, indicating that digital transformation of enterprises affects performance improvement through the enterprise efficiency path. Combined with the empirical results of the benchmark regression 1, the total asset turnover is verified as an influential mediation variable, effectively confirming H2, indicating that digital transformation promoted efficiency and indirectly improved enterprise performance.

Based on the above analysis, this study evaluates the second path of digital transformation of manufacturing enterprises, the mediation effect of the cost rate. The results are presented in Table no. 4.

Table no. 4. Mediation Effect Test for Cost Reduction

Variable	ROA	ROE	Cost Rate
	8	9	10
Digital Transformation	0.0068* (1.79)	0.0260* (2.41)	-0.0266*** (-4.30)
Cost Rate	-0.4066*** (-16.76)	-0.9198*** (-13.32)	-
Control	Yes	Yes	Yes
Constant	0.1135* (0.59)	0.4176 (0.77)	2.0687*** (6.77)
Time (Entity) Fixed	Yes	Yes	Yes
Observation	780	780	780
R ²	0.4298	0.3012	0.1206

Note: Robust t-statistics in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

In regression 10, the coefficient of the digital transformation variable of manufacturing companies is -0.0266 , which is significant at the 1% level, indicating that the digital transformation of manufacturing companies significantly inhibits the increase in the cost rate. The results of regressions 8 and 9 demonstrate that the cost rate has a negative and significant impact on the enterprise performance, indicating that effective cost control is beneficial in improving the enterprise performance. The explanatory core variable, the digital transformation, is positive. The empirical results of benchmark regressions 1 and 3 verified that the cost rate is an effective intermediary variable, affirming H3. Furthermore, if cost increases due to the digital transformation of the enterprise, it will have a negative impact on performance, confirming H1b.

3.5. Threshold Effect Tests

Considering that improvements in the digital transformation of manufacturing companies involve a long and gradual process, the initial digital transformation may not only open new markets for manufacturing companies, but also affect the performance of companies due to the high initial cost of such transformation. To address this, in this study, the panel threshold model is used to analyse the impact of different levels of digital transformation on the performance of manufacturing enterprises. Specifically, the Bootstrap method is used to sample and estimate the critical value of the threshold variable under significant conditions (limited to the length of the article; the results can be obtained from the author). The results of the sampling test reveal a significant two-way threshold effect on the level of digitalisation of manufacturing companies, where the single threshold value is 1.0986, and the P-value is not significant. The double threshold value is 3.0910, which is significant at the 10% level; therefore, the double threshold effect is congruent with the model setting (4).

Table no. 5. Estimated Value of the Panel Threshold Model Variable

	Estimated Coefficient	T Statistic Value	Standard Error	P Statistic Value
$Q / D_1 \leq D_1 /$	0.0157	0.82	0.82	0.411
$Q / D_1 \leq D_1 \leq D_2 /$	0.0214	4.17	4.17	0.000
$Q / D_1 \geq D_2 /$	0.0148	3.12	3.12	0.002
Other Control Variable	Control			
Time (Entity) Fixed	Yes			
R ²	0.1776			

Note: Robust t-statistics in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The differences in variable estimation for the panel threshold model (Table no. 5) reveal that the effect of digitisation on enterprise performance is limited by the degree of enterprise digitisation. Only when the digitalisation of manufacturing enterprises reaches a stage can digital transformation have a significant positive impact on performance. When the level of digital transformation of the manufacturing industry is less than 1.0986, the estimated coefficient of digital transformation is 0.0157, which is not significant. When the level of digitisation of the second stage is more significant than 1.0986, and less than 3.091 and the level of digitisation of enterprises in the third stage is more significant than 3.091, digital transformation will have a positive effect on the performance of manufacturing enterprises, and the result will be significant at the 1% level.

The digitisation of many manufacturing enterprises in China is still in the preliminary stage. Despite massive investment in integrated digital transformation, there is no immediate effect (i.e., input efforts and output products are not proportional). Therefore, the integration of digital technology and business production does not work well during this transition period. In the second stage of digital transformation, with the deep integration of digital technology, manufacturing enterprises can skilfully transform traditional business models, increase efficiency, and reduce fees using digital technology, ultimately improving enterprise performance. Based on this finding, H4 is verified.

The digital transformation of manufacturing enterprises exerts a threshold effect. In the early stage of the digital transformation of manufacturing enterprises, the degree of digital transformation is relatively low and will not bring substantial increases in enterprise performance. However, as the digital degree passes the first threshold, it will demonstrate a significant positive impact, demonstrating that digital transformation has the advantage of backwardness over traditional economic transformation.

3.6. Heterogeneity Analysis

It is worth exploring whether the digital transformation of a manufacturing enterprise is heterogeneous. Heterogeneity analysis is conducted from two perspectives based on the characteristics of the company by taking a microview. (1) Based on the characteristics of the ownership form of the enterprises, the samples are divided into state-owned and private-owned enterprises. (2) Based on the business scale of the company with its average asset size measured during the observation period, the samples are categorised into large, medium, and small enterprises.

The first analysis is based on differences in enterprise ownership. Digital transformation is found to significantly improve the performance of both state-owned and private-owned enterprises; the effect on the former is relatively better. This result could be that the digital transformation of enterprises requires a wide range of digital technology applications and large-scale investment in intelligent manufacturing and establishing a modernised information system. State-owned companies enjoy the advantages of financial strength, business scale, scientific research power, and favourable policies. Conducting digital transformation could enrich the capacities of state-owned enterprises. These enterprises could implement digital strategies with comparative advantages to effectively compensate for efficiency losses and push for high-quality development, which presents an essential reference for reforming state-owned enterprises.

The second analysis assesses the differences on the business scale. Referring to the Measures for Classifying Large / Medium / Small Enterprises Statistically, released by the National Bureau of Statistics of China, samples are divided into sizes according to the number of employees and the income of the companies.

The digital transformation of large manufacturing enterprises significantly improves performance, whereas the digital transformation of small and medium enterprises has no significant impact on performance. This result could be that digital transformation can exert a scale effect; the more significant an enterprise is on scale, the easier it can deliver its “power” in digitalisation. Although the digital transformation of an enterprise could help improve performance, specific prerequisites, such as technology, labour force, and capital, are required. Compared to large and medium enterprises, small companies have a scarcity of production factors, such as the technological base and human and physical capital. Overemphasising digital transformation can lead to an enterprise’s digital technology and data resources being incompatible with other factors, resulting in insignificant performance. This explains that the digital transformation of enterprises should be carried out moderately, according to the overall resources of the enterprise and the level of production factors. Blindly improving digitalisation would not be conducive to the development of an enterprise (Table no. 6).

Table no. 6. Heterogeneity Tests

Classification Basis	Classification by ownership				Classification by size			
	State-owned companies		Private companies		Large companies		Small and medium companies	
	Roa	Roe	Roa	Roe	Roa	Roe	Roa	Roe
Digital Transformation	0.0160*** (2.78)	0.0668** (2.43)	0.0143** (2.41)	0.0301** (2.49)	0.0138*** (3.44)	0.0485*** (3.93)	0.0267 (1.27)	0.0248 (0.64)
Entity Fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed (Year)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
adj R2	0.104	0.1539	0.2309	0.2318	0.1443	0.1629	0.2982	0.3985
Observation	245	535	245	535	675	105	675	105

Note: Robust *t*-statistics in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4. Discussion and Conclusions

This study studies the influence of digital transformation on manufacturing companies. Based on competitive advantage and from the perspective of efficiency and cost, the intermediary effect model investigates the intermediary effect between them. Furthermore, based on path dependence theory, the influence of different levels of digital transformation on manufacturing enterprises is investigated through a panel threshold model. The results demonstrate that the impact of digital transformation on the performance of manufacturing enterprises is not only direct, but also indirect. At the same time, the effect of digital transformation on the performance of manufacturing enterprises has a threshold effect. From the perspective of the promotion of digital transformation, the lower digital level of an enterprise will not effectively increase performance. With improvement in the digital level, the positive role of digital transformation becomes more prominent.

Our research guides future research on the impact of digital transformation on enterprise performance. It also constructs quantitative indicators for enterprise digital transformation researchers and a guide to examine the unknowns of action mechanisms. More extensive and sufficient research is expected to be conducted. Our study offers new perspectives on the development of strategies for governments and manufacturing companies around the world. Although data from Chinese mainland enterprises were used, different sample data from various countries will be used in further studies.

Research findings are of practical significance to policy makers and manufacturing enterprises. We suggest that manufacturing enterprises strive to improve digital transformation levels and fully leverage digital technology capabilities to promote intensive production and management to simultaneously reduce enterprise costs and losses in internal efficiency. For example, manufacturing enterprises can formulate long-term and dynamic digital transformation strategies. Policy makers can promote incentives policies and measures to improve the levels of digital transformation of manufacturing enterprises. At the same time, local governments can assist small and medium companies in digital transformation to encourage an inclusive and collaborative digital economy industrial ecology of large, medium, and small companies.

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