*Corresponding Author’s Email: 1146889390@qq.com
Proceedings of the International Conference on Applied Research in Management, Business and Economics,Vol. 2 Issue. 2, 2025, pp. 11- 34
DOI: https://doi.org/10.33422/icarbme.v2i2.1908

ISSN: 3030-1149 online

A Study of the Impact of Digital Transformation on Business Performance in Manufacturing Enterprises

Heng Ma, and Suyan Gong
College of Economics and Management, Nanjing University of Aeronautics and Astronautics, China

Abstract

Amid the revolution in information technology, the digital transformation of manufacturing is reshaping traditional production models toward smart systems. While existing research has explored industrial digitalization at a macro level, systematic studies on how micro-level manufacturing firms evolve in performance and innovation during this process remain limited. This article aims to reveal the performance changes of manufacturing enterprises during digital transformation and examine the dynamic interaction between these changes and technological innovation capability. The study constructs a multi-level framework linking “digital transformation - innovation capability - corporate performance” focusing specifically on the mediating role of innovation capability in the transformation-performance relationship and comparing heterogeneous effects across ownership types and geographic regions. Using data from Chinese A-share listed manufacturing companies from 2019 to 2023, the research applies empirical modeling to test the proposed relationships. Findings indicate that digital transformation significantly enhances corporate performance, with innovation capability playing a crucial mediating role. Heterogeneity analysis shows that state-owned enterprises experience stronger performance gains than non-state-owned firms, and companies in central and western China benefit more than those in the eastern region. Based on these results, the study offers practical policy recommendations to support effective digital transformation in manufacturing.

Keywords: Digital Transformation, Business Performance, Manufacturing Companies

1. Introduction

The manufacturing industry occupies a pivotal strategic position in the national economic system and is the core force supporting the healthy development of the real economy. In the new stage of rapid development of the digital economy, modern information technology represented by artificial intelligence and industrial internet is accelerating the deep integration with the traditional manufacturing system, giving rise to the new production paradigm of intelligent manufacturing. This industrial paradigm shift effectively addresses pressing challenges such as escalating labor costs and increasing resource and environmental constraints by reconfiguring production methods and operation modes. Manufacturing enterprises have not only optimized the efficiency of resource allocation, but also significantly enhanced their innovation vitality and market competitiveness by increasing their investment in digital technology and promoting the intelligent transformation of the entire value chain, ultimately realizing an overall improvement in the quality of their operations.

Regarding the relationship between enterprise digitalization input and enterprise performance, there are different theoretical views in the academic world. Mainstream research generally confirms that the application of digital technology can significantly improve enterprise performance, but some scholars based on the phenomenon of "productivity paradox" questioned that the relationship between technological inputs and performance improvement is not a simple linear relationship. In addition, the existing literature has provided a multi-dimensional analysis of the path of digital transformation, which involves the optimization of operational efficiency, the cultivation of innovation capacity and other intermediary mechanisms. However, there are still some limitations in the research on the economic consequences of digitalization investment: first, the intrinsic mechanism needs to be explored in depth; second, there is a lack of systematic verification of the differences in the applicability of the industry.

2. Literature Review

2.1 Review of Previous Research

2.1.1 Performance Dividends of Digital Transformation

The positive impact of digital transformation on corporate performance has achieved a broad consensus in academia. From a technology-enablement perspective, digital upgrades allow companies to secure sustainable competitive advantages and profit growth (Bughin, 2023). Conceptualizing this transformation as a dynamic process, Vial (2019) notes that digital technologies prompt organizations to adopt strategic responses to alter value creation pathways and manage structural changes and organizational barriers. At the operational level, this process can be structured into three measurable stages: stand-alone, integrated, and autonomous tools. Rather than yielding mere incremental process improvements, successful transformation fosters business model innovation, thereby enhancing organizational responsiveness and flexibility (Angelopoulos et al., 2023).

Empirical evidence further highlights various underlying financial and localized mechanisms across the manufacturing sector. Financially, digitalization improves performance by reducing corporate financial, operating, and combined leverage (Hu et al., 2024). In the context of Industry 4.0, Dalenogare et al. (2018) examined Brazilian manufacturing firms and found that certain Industry 4.0 technologies exert a positive promoting effect on industrial performance. From a micro-operations management perspective, Smith et al. (2024) investigated U.S. manufacturing firms to explore how Industry 4.0 technologies, such as big data collection and processing, optimize production performance through "Digital Performance Management" tools, thereby resolving the data obfuscation issues inherent in traditional metrics like Overall Equipment Effectiveness.

Furthermore, these digital capabilities significantly empower outward market performance and multidimensional sustainability. Based on primary data from the Jordanian manufacturing sector, Al Khatib (2024) empirically demonstrated a positive correlation between big data analytics capability and export performance, with supply chain innovation acting as a key mediator. Focusing on small and medium IT firms in Malaysia, Khin and Ho (2019) observed that digital orientation and digital capability positively affect digital innovation, which subsequently mediates the impacts of technological orientation and digital capability on both financial and non-financial performance. Regarding ecological and economic outcomes, Buhaya and Metwally (2024) investigated Egyptian manufacturing companies and found that core digital technologies—namely blockchain, IoT, big data analytics, cloud computing, and digital twins—exert a positive impact on environmental, social, and economic sustainability.

2.1.2 Boundary Conditions and Managerial Challenges

Despite these documented benefits, the implementation of digital transformation introduces severe managerial and operational challenges, and its returns are highly conditional upon external and internal attributes. Structurally, firm size dictates the feasibility of technology adoption; Horváth and Szabó (2019) revealed that multinational corporations possess stronger driving forces and face lower implementation barriers in promoting Industry 4.0 compared to small and medium-sized companies. For firms that do engage in transformation, scholars note that high delivery process efficiency remains a core prerequisite (Li et al., 2024), and embedded servitization plays a positive mediating role in determining final rewards (Yu et al., 2024). Additionally, there is a moderate positive correlation between baseline digital capabilities and corporate performance (Ma and Wang, 2025).

To unlock these dividends, specific internal alignments and organizational conditions must be meticulously established. Analyzing 183 Spanish SMEs across different industries, Orero Blat et al. (2024) emphasized the necessity of creating specific conditions to enable digital transformation to generate a positive impact on performance. Investigating manufacturing firms in Saudi Arabia, Binsaeed et al. (2023) identified that big data analytics capability plays a crucial role in the development of innovation performance, highlighting that its efficacy relies heavily on the specific roles of organizational readiness and digital orientation. In terms of strategic alignment, Turkcan et al. (2025) empirically demonstrated that digital capabilities indirectly influence the environmental and economic performance of manufacturing firms through the mediation of circular economy practices, accentuating the vital role of alignment between digital technology and environmental strategies. Turkcan (2025) further found that green product innovation and digital transformation jointly strengthen the impact of sustainable manufacturing practices on the financial performance of manufacturing firms. Similarly, Lima et al. (2025) examined Brazilian manufacturing enterprises and determined that the alignment and synergy between front-end digital technologies and Just-in-Time practices exert a positive moderating effect on operational and economic performance returns. To systematically gauge these interactions, Fortier et al. (2025) constructed a framework for Canadian manufacturing SMEs enabling firms to simultaneously assess their digital maturity and its impacts on sustainable performance dimensions, underscoring the importance of incorporating sustainability into digital transformation strategies.

Without these tailored strategies and capabilities, digital investments frequently trigger operational risks and diminishing returns. Wu et al. (2024) observed that while digital transformation boosts economic performance, these positive effects are not more pronounced in firms with already higher baseline performance, though the depth of transformation significantly enhances performance. Wang et al. (2020) warned that poorly executed digitalization can decrease the return on infrastructure investment, turning technology into a rigid cost burden. Qi and Cai (2020) further pointed out that if management capabilities lag behind technological integration, deep assimilation into business processes fails. Finally, external environmental factors heavily influence these driving mechanisms and outcomes (Zhai et al., 2021), and the required resource investments may trigger temporary fluctuations in operational efficiency that demand careful management oversight.

2.1.3 Summary of literature review

In summary, while extensive research has established systematic measurement frameworks and dimensional classifications in this field, empirical conclusions remain divergent. Some scholars remain skeptical about the linear benefits of digitalization, suggesting instead a non-linear relationship with corporate performance. This fragmentation offers limited actionable guidance for corporate practice. Crucially, a significant research gap persists regarding the manufacturing sector, particularly at the micro-enterprise level. To address these limitations, this paper investigates digital transformation within the manufacturing sector. By delving into the specific pathways and underlying mechanisms through which digitalization impacts the business outcomes of manufacturing firms, this study provides an innovative empirical framework to accelerate the integration of digital and real economies.

2.2 Research hypotheses

2.2.1 The Relationship Between Digital Transformation and Corporate Performance in Manufacturing Enterprises

The rapid development of next-generation information technologies is reshaping corporate value creation models. Digital transformation optimizes resource allocation and operational efficiency by reducing agency costs and alleviating information asymmetry. At the same time, through digital transformation, enterprises can access additional sources of knowledge and information, thereby securing more resources and enhancing their competitiveness. Specifically, its mechanism of action is primarily reflected in the following three aspects:

First, digital empowerment expands enterprises' channels for acquiring resources. Research by Bag et al.(2021) found that by leveraging the network effects and agglomeration functions of digital technology, enterprises can break through traditional resource constraints and access a richer array of knowledge elements and information capital. Second, digital transformation optimizes operational management systems. By establishing a unified data center, enterprises effectively resolve the issue of fragmented cross-departmental information and eliminate "information silos." Yuan et al.(2021) further point out that digitalization also drives organizational structures toward a flatter hierarchy, achieving the integration and optimization of management processes, and significantly reducing organizational operating costs. Third, digital applications enhance information transparency. Empirical research by Li et al.(2023) indicates that the application of digital technologies can effectively mitigate information asymmetry, reduce coordination costs and default risks during transactions, thereby improving corporate operational efficiency and market competitiveness.

In summary, digital transformation will be an indispensable component of a company's future development, exerting a significant impact on corporate performance. Following digital transformation, enterprises send positive signals to the market, making it easier for them to secure financial support and obtain favorable loan terms, thereby creating a favorable financial environment for improving corporate performance.

Therefore, this paper proposes the following Hypothesis 1:

H1: Digital transformation in manufacturing enterprises contributes to improved corporate performance.

2.2.2 The Mediating Role of Corporate Innovation Capacity

The fundamental driving force behind a company's sustainable development lies in the cultivation of its innovation capacity. To implement an innovation-driven development strategy, it is essential to break down the institutional barriers that constrain technological R&D and industrial application. Existing literature primarily analyzes the intrinsic mechanisms through which technological innovation and institutional reform work in tandem to drive industrial upgrading. Chen et al.(2019) argue that the digital transformation of manufacturing enterprises can enhance innovation levels, thereby positively influencing improvements in corporate performance. Yang et al.(2023), in exploring the mechanism by which digitalization levels influence corporate performance, also found that the complementarity of dual innovation plays a partial mediating role between digitalization levels and corporate performance. Zhang and Gu(2023) similarly found that, in terms of the concrete manifestations of corporate innovation activities, digital capabilities can promote the continuous improvement of corporate performance through the mediating mechanism of facilitating open innovation.

Digital transformation primarily promotes corporate innovation through the following four aspects: First, enterprises have recognized the importance of accelerating digital transformation and are consciously innovating to adapt to the external environment with the advent of the digital wave. Second, digital development can effectively activate the innovative momentum of manufacturing enterprises; this influence spans multiple levels, including product design, management models, and organizational structures, providing continuous momentum for the evolution of the industrial innovation ecosystem. Third, based on the unique precision, stability, and efficiency advantages of digital technologies, manufacturing enterprises can gain significant technological empowerment during the innovation process, which provides a solid foundation for the conduct of innovation activities. Fourth, by reshaping the consumer market landscape, the digital economy has significantly enhanced the pull effect on the demand side. By leveraging digital tools to integrate and analyze end-market and user data, manufacturing enterprises can achieve precise demand forecasting, driving the transformation of R&D models from traditional experience-based approaches to data- and intelligence-driven ones.

In summary, there is a significant positive correlation between the evolution of innovation factors and the development of the digital economy. Digital transformation provides enterprises with technical support and data-driven decision-making capabilities, enabling them to conduct exploratory and exploitative innovation more efficiently, while the enhancement of innovation capabilities further translates into competitive advantages and improved financial performance.

Therefore, this paper proposes the following Hypothesis 2:

> H2: Corporate innovation capabilities play a mediating role in the process by which digital transformation in manufacturing enterprises enhances corporate performance.

3. Results and Discussion

3.1 Research Sample and Data Sources

In this paper, according to China's National Economic Industry Classification (GB/T 4754-2017), manufacturing enterprises are screened from China's Shanghai and Shenzhen A-share listed enterprises from 2019 to 2023 as the research object.

On this basis, this paper carries out the following treatments for the initial sample: first, the observations with missing values of key financial indicators exceeding 50% are deleted; second, the listed companies with special treatment ST and ∗ST implemented during the study period are excluded; third, the samples of enterprises with negative net assets are excluded; and lastly, all continuous variables are subjected to a bilateral shrinkage process at the 1% quartile. After the above screening process, the final research sample containing 279 listed companies with a total of 1,395 observations is obtained.

The degree of digital transformation is from the Collaboration Database in the CSMAR database, financial indicators related to firm performance are from the Financial Indicators

Analysis in the CSMAR database, and all other data are from the Accounting Information Quality module in the CSMAR database.

3.2 Description of key variables

3.2.1 Explained Variable

In order to make the measurement of indicators more scientific and rigorous, and the conclusion closer to the industrial reality, and enhance the significance of guidance to enterprises, this paper is based on the indicator system of the State Council's "Interim Measures for the Management of the Comprehensive Performance Evaluation of Central Enterprises", and refers to the practice of scholars such as Chen et al.(2020), to select the evaluation indexes from the dimensions of profitability, operating ability, solvency, and development ability, and to use the entropy weighting method to determine the weight of each index as a measure of enterprise performance. The entropy weight method is used to calculate and determine the weight of each indicator as a measure of corporate performance, see Table 1:

Table 1: Evaluation System Weights

Variables		Indicators	Indicator Explanation	Weights
Firm Performance (FirmPerf)	Profitability (PF)29.5%	Return on Net Assets	Net Profit/Average Assets	36.61%
		Net Operating Margin	Net Profit/Operating Income	63.39%
	Operating Profitability (OP) 22.6%	Total Asset Turnover	Net Operating Income/Average Assets	36.88%
		Accounts Receivable Turnover	Net Operating Income/Average Accounts Receivable Balance	63.12%
	Debt-servicing capacity (DB) 25.8%	Asset-liability ratio	Total liabilities/total assets	54.99%
		Current ratio	Current assets/current liabilities	45.01%
	Developing capacity (DP)22.1%	Growth rate of operating income	(Current amount of operating income- Previous amount)/Previous amount	50.37%
		Capitalization ratio	Owner's equity at the end of the period/owner's equity at the beginning of the period	49.63%

Source: Author's calculations

3.2.2 Explanatory Variables

Digital transformation has turned out to be a key link in the current promotion of high-quality development of the economy, and at the same time, it is also a core strategy for the growth of the enterprise, which is particularly important in the context of the digital economy. For the assessment of digital transformation, there exists a diversified system of measurement methods in academia. Some scholars reflect the level of technological investment by calculating the proportion of intangible assets in total assets, which focuses on the asset value of informatization systems and software applications. Other scholars use comprehensive performance evaluation tools to examine the digitalization process of an organization from multiple dimensions. In addition, text analysis methods based on the content of annual reports have been widely used to quantify the degree of digitalization construction of an enterprise, and this method obtains assessment data through technical means such as keyword extraction and semantic analysis. In this paper, we refer to Wu et al.(2021) who explored the impact of SMEs' digital transformation on corporate performance by using the text mining method of corporate annual reports. As a statutory disclosure document, corporate annual report systematically records the organization's business results and future development strategy layout during the reporting period. The frequency of keywords in specific fields in the annual report can effectively reflect the enterprise's resource investment and development level in the field. In constructing the digital assessment system, the method based on text analysis has significant advantages over traditional indicators: first, it relies on audited public annual report data to ensure the reliability and accuracy of the information source; second, multi-dimensional semantic analysis can comprehensively grasp the various dimensions of the enterprise's digital construction.

This paper adopts the following steps to construct digital indicators: First, a feature vocabulary is scientifically constructed and classified. In identifying feature terms related to enterprise digital transformation, this paper employs a method that combines an "academic literature-oriented" approach with "authoritative policy-driven" guidance. On the one hand, it draws upon classic literature in the field of digitalization, such as Li et al. (2020) and Ling et al. (2021); on the other hand, it closely integrates authoritative policy documents such as the "Special Action Plan for Digital Empowerment of Small and Medium-Sized Enterprises" and the "Implementation Plan for Promoting the Cloud Adoption, Data Utilization and Intelligence Empowerment Initiative to Foster New Economic Development"issued by China's Ministry of Industry and Information Technology and other ministries, the "2020 Digital Transformation Trends Report" by the China Academy of Information and Communications Technology, and the annual "Government Work Reports". Through text mining and expert review, the Digital Transformation Keyword Library shown in Table 2 was ultimately developed. Next, the text underwent fine-grained noise removal, word segmentation, and homonym identification. Since direct full-text string matching is prone to truncation errors or contextual bias, this study first utilized the "Jieba" package in Python to perform precise tokenization on the annual reports of the sample enterprises from 2019 to 2023, removing standard stop words, numbers, punctuation, and redundant headers and footers. To address the common issues of polysemy and contextual confusion in text metering, this paper not only rigorously excludes the semantic expressions of negative terms preceding keywords through forward and backward text matching, but also, through manual spot-checking and contextual verification, precisely filters out digital descriptions unrelated to the company's current business operations—including background information on major shareholders, customers, and suppliers, as well as employment history in executive resumes—to ensure that word frequency counts are entirely focused on the sample company's own implementation of its digital strategy. Finally, we constructed indicators and addressed disclosure biases. Based on the results of word segmentation and matching, we categorized and aggregated word frequencies related to key technology directions and summed them across the entire text. Given that text word frequency data typically exhibits a right-skewed distribution, to stabilize the variance and achieve reasonable cross-company data scaling, this study applied a $ln\,(\,total\ word\ frequency{+}1)$ transformation to the original total word frequency, deriving a continuous variable that characterizes a company's digital transformation. Furthermore, although management may engage in disclosure bias—such as strategically exaggerating achievements or withholding information on digital transformation due to trade secrets—in annual report disclosures, the solemn nature of annual reports as legally mandated disclosure documents subjects them to strict constraints from external independent audits and heavy penalties from regulatory authorities for false statements. These legal constraints significantly curb systematic misreporting, thereby ensuring that the digital transformation indicators extracted from annual reports through text mining in this study possess a high degree of reliability and empirical robustness.

Table 2: Digital transformation keyword library

Classification	Keywords
Artificial Intelligence Technology	Artificial Intelligence, Business Intelligence, Image Understanding, Investment Decision Aid System, Intelligent Data Analytics, Intelligent Robotics, Machine Learning, Deep Learning, Semantic Search, Biometrics, Face Recognition, Speech Recognition, Identity Authentication, Autonomous Driving, Natural Language Processing
Big Data Technology	Big Data, Data Mining, Text Mining, Data Visualization, Heterogeneous Data, Credit, Augmented Reality, Mixed Reality, Virtual Reality
Cloud Computing Technologies	Cloud computing, streaming computing, graph computing, in-memory computing, multi-party secure computing, brain-like computing, green computing, cognitive computing, converged architectures, billion-level concurrency, EB-level storage, Internet of Things, information physical systems
Blockchain Technologies	Blockchain, digital currency, distributed computing, differential privacy technology, smart financial contracts
Digital Technology Application	Mobile Internet, Industrial Internet, Mobile Internet, Internet Healthcare, E-commerce, Mobile Payment, Third-party Payment, NFC Payment, Smart Energy, B2B, B2C, C2B, C2C, O2O, NetUnion, Smart Wearable, Smart Agriculture, Smart Transportation, Smart Customer Service, Smart Healthcare, Smart Home, Smart Investment, Smart Literature and Tourism, Smart Environmental Protection, Smart Grid, Intelligent Marketing, Digital Marketing, Unmanned Retail, Internet Finance, Digital Finance, Fintech, Fintech, Quantitative Finance, Open Banking

Source: Adapted from Li et al. (2020) and Ling et al. (2021)

3.2.3 Mediating Variables

As the knowledge system and skill sets formed by organizations in the process of technological innovation throughout the entire value chain of R&D and design, production and operation, and market development, there are mainly two theoretical perspectives in the academic community, namely, the technological absorption and improvement view which emphasizes the ability of digesting and re-creating the existing technology and the innovation output performance view which is measured by the number of patents granted and the development of new products. In this paper, we refer to Cen and Chen's approach (2019), which takes the number of patents belonging to the new technology field applied successfully by the enterprise each year plus one to take the logarithm of the number of patents as a measure of the enterprise's innovation capability.

3.2.4 Control Variables

This paper draws upon the methodologies employed by Sun and Wang (2017), Lin and Wu (2021), Ye et al. (2016), selecting the following variables as control variables for the empirical research.

(1) Firm Size (Size)

As a key organizational characteristic, firm size exerts a systematic influence on the scope of business operations and strategic choices. The theory of economies of scale suggests that larger firms typically achieve more significant cost savings and possess stronger market bargaining power, factors that substantially impact financial performance. Therefore, to control for potential confounding effects associated with firm size, this study uses the natural logarithm of a firm's total assets at the end of the period as a proxy for firm size and treats it as a control variable.

(2) Firm Age (Age)

The duration of a firm's listing exhibits a significant correlation with its industry influence and operational maturity. Differences in firm longevity lead to marked variations in their responsiveness to technological change. This dynamic adaptability both constrains the depth of organizational transformation and influences operational performance outcomes, warranting its inclusion as a control variable. Therefore, this study employs the natural logarithm of a firm's listing duration as a measure of firm age and incorporates it as a control variable.

(3) Two Roles in One (Dual)

Within corporate governance structures, when the board chair concurrently serves as chief executive officer, this dual role arrangement significantly enhances the decision-making autonomy of the executive team. This arrangement may induce agency problems and heighten the risk of financial misconduct, potentially impacting accounting performance.Therefore, a dummy variable is constructed: it is assigned a value of 1 if the board chairman concurrently serves as the chief executive officer, and 0 otherwise.

(4) Equity Concentration (Top10)

The characteristics of equity structure effectively reflect the allocation of corporate ownership, particularly under the modern corporate system where ownership and management rights are separated. The shareholding ratio of major shareholders has become a key dimension for measuring governance effectiveness. Given the significant correlation between corporate governance quality and financial performance, the degree of equity concentration indirectly influences corporate economic outcomes through the governance mechanism. Therefore, this paper adopts the shareholding ratio of the top 10 shareholders as a measure of equity concentration and uses it as a control variable.

(5) Audit Opinion (Audit)

The audit opinion serves as the professional attestation of an accounting firm regarding an enterprise's financial reporting. Therefore, this paper adopts the orderly assignment method to quantify the type of audit opinion and takes it as a control variable: the standard unqualified opinion is assigned as 1, the unqualified opinion containing explanatory notes is assigned as 2, the qualified opinion is assigned as 3, and the simultaneous existence of qualified opinion and emphasis of matter paragraph is assigned as 4.

3.3 Model Construction

3.3.1 Standardized Regression Model

According to the Hypothesis 1 proposed in this paper, to test the mechanism of the impact of digital transformation of manufacturing enterprises on their enterprise performance, this paper constructs the following regression model (1), in which i and t represent firms and years, respectively. The dependent variable, $FirmPerf_{i,t}$, measures the performance of sample firm i in year t, and the key explanatory variable, $Digital_{i,t}$, captures its concurrent digital transformation. $Controls_{k,i,t}$ denotes a set of firm-level control variables, with β_k being the estimated coefficients.To address omitted variable bias, we include firm fixed effects (μ_i) and year fixed effects (λ_t) to account for time-invariant firm characteristics and macro time trends, respectively. α_0 and $\varepsilon_{i,t}$ denote the constant and the random error term, respectively. The primary parameter of interest is α_1. A significantly positive estimate of α_1 suggests that accelerating digital transformation significantly boosts the performance of publicly listed manufacturing firms.

$$FirmPerf_{i,t}=\alpha_0+\alpha_1 Digital_{i,t}+\sum \beta_k\, Controls_{k,i,t}+\mu_i+\lambda_t+\varepsilon_{i,t} \quad (1)$$

3.3.2 Mediation effect model

According to Hypothesis 2 proposed in this paper, to test the mediating effect of firms' innovation capability ($Median_{i,t}$) in the relationship between digital transformation and firm performance, this paper constructs the two-way fixed effects specifications in Equations (2) and (3). In these models, i and t denote firms and years. $Median_{i,t}$ measures the innovation level of firm i in year t.$Controls_{k,i,t}$ is a vector of firm-level controls, with γ_k and η_k being their respective coefficients. β_0 and θ_0 are constants, and $\varepsilon_{i,t}$ and $v_{i,t}$ are random disturbances.

To address omitted variable bias and unobserved confounders, we include both firm fixed effects (μ_i) and year fixed effects (λ_t) to absorb time-invariant firm attributes and macro time trends, respectively. The mediation effect holds if : (1) digital transformation significantly boosts innovation capacity (β_1>0 significantly); and (2) conditional on innovation capacity, the direct impact of digital transformation (θ_1) remains significant, or innovation capacity itself significantly and positively affects firm performance (θ_2>0 significantly).

$$Median_{i,t}=\beta_0+\beta_1 Digital_{i,t}+\sum \gamma_k\, Controls_{k,i,t}+\mu_i+\lambda_t+\varepsilon_{i,t} \quad (2)$$

$$FirmPerf_{i,t}=\theta_0+\theta_1 Digital_{i,t}+\theta_2 Median_{i,t}+\sum \eta_k\, Controls_{k,i,t}+\mu_i+\lambda_t+v_{i,t} \quad (3)$$

3.4 Empirical Analysis

3.4.1 Descriptive Statistics

In this paper, descriptive statistics of the core and control variables of the target companies during the period of 2019 to 2023 were conducted. According to the descriptive statistics in Table 3, the sample of this paper contains 1395 valid observations. The basic statistical characteristics of each variable are presented through the indicators of concentration trend and discrete degree. The statistical analysis of the level of digital transformation shows that its mean value is 3.084, the distribution interval is [0, 5.878], and the median is 3.136. This result reflects the significant heterogeneity of different enterprises in terms of digital transformation. In terms of enterprise performance, the mean value of the observed variables reaches 1.139, with a range of values from 0.397 to 3.354 and a median of 1.020. The data distribution characteristics indicate that the operational performance of the sample enterprises shows obvious polarization, and some enterprises face greater operational difficulties.

Table 3 Descriptive Statistics

Variables	Sample size	Mean	Standard deviation	Minimum	Median	Maximum
Digital	1395	3.084	1.154	0.000	3.136	5.878
FirmPerf	1395	1.139	0.478	0.397	1.020	3.354
Size	1395	23.102	1.287	20.151	22.952	27.638
Age	1395	3.085	0.234	1.992	3.099	3.662
Dual	1395	0.704	0.457	0.000	1.000	1.000
Top10	1395	52.115	15.532	8.780	51.290	96.350
Audit	1395	1.033	0.240	1.000	1.000	4.000

Source: Author's calculations

3.4.2 Relevance Analysis

Based on Stata statistical software, this paper tests the correlation between the variables. As shown in Table 4, the results of the correlation analysis indicate that there is a significant positive association between the level of digital transformation (Digital) and the corporate performance indicator (FirmPerf) at the 1% confidence level, a result that supports the validity of the initial theoretical expectations. In addition, the degree of association between each control factor and the core explanatory variables meets the statistical requirements, and this result indicates that the research model has good variable identification ability.

Table 4 Correlation Analysis

	Digital	**FirmPerf**	**Size**	**Age**	**Dual**	**Top10**	**Audit**
Digital	1						
FirmPerf	0.155***	1					
Size	0.187***	0.036	1				
Age	-0.002	-0.010	0.181***	1			
Dual	-0.093***	-0.078***	0.106***	0.120***	1		
Top10	-0.139***	0.206***	0.230***	-0.125***	0.084***	1	
Audit	0.029	-0.104***	-0.051*	0.052*	0.000	-0.056**	1

Source: Author's calculations

3.4.3 Regression Analysis

(1) Main Effect

This paper empirically analyzes a sample of manufacturing firms using a panel data fixed-effects model, and the specific regression results are detailed in Table 5. Column (1) contains only year and individual fixed effects, and the estimated coefficient of the level of digital transformation (Digital) is 0.0429, which reaches the level of statistical significance of 1%. After introducing the full set of control variables in column (2), the estimated coefficient of Digital transformation level remains at 0.0353, still showing a significant positive effect. This indicates that manufacturing firms obtain significant improvement in their business results after implementing digital transformation, i.e., Hypothesis 1 is verified.

Table 5 Main effects test

Variables	**(1)FirmPerf**	**(2)FirmPerf**
Digital	0.0429***	0.0353**
	(0.0157)	(0.0161)
Size		-0.0233
		(0.0340)
Age		0.3397**
		(0.1631)
Dual		0.0520*
		(0.0275)
Top10		0.0001
		(0.0016)
Audit		-0.0245
		(0.0344)
_cons	1.0104***	0.4583
	(0.0487)	(0.7931)
Year fixed effect	Yes	Yes
Company fixed effect	Yes	Yes
N	1395	1395
adj. R^2	0.7831	0.7850

Standard errors clustered at the firm level are reported in parentheses

Source: Author's calculations

(2) Mediation Effect

In this paper, we adopt the Bootstrap method recommended by Hayes(2009) to test the mediating effect of innovation capability, and the specific operational settings are as follows: set the sampling number to 2000 and the confidence interval to 95%. The judgment criteria are: when the lower and upper confidence intervals of the indirect effect do not contain 0, the existence of the mediating effect is confirmed; if the confidence interval of the direct effect contains zero values, the mediating effect is judged to be complete; otherwise, if both indirect and direct effects are significant, it is a partial mediation.

As shown in Table 6, the 95% confidence intervals for the indirect effect [0.004, 0.043] and t he direct effect [0.038, 0.113] in the Bias-corrected model do not include 0. Furthermore, the 95% confidence intervals for the indirect effect [0.003, 0.042] and the direct effect [0.035, 0.1 11] in the percentile method also do not include 0, which confirms a typical partial mediation mechanism, indicating that digital transformation not only directly drives manufacturing perfo rmance but also indirectly enhances it by optimizing the underlying path of innovation capabil ity. The underlying standardized path coefficients for *Digital→Innovation capability* (Path *a*) and *Innovation capability→FirmPerf* (Path *b*) are 2.7977 and 0.0072 respectively, with their p roduct ($a\times b$=0.020) perfectly corresponding to the bootstrapped indirect effect.

Table 6 Mediated effects test

Effect	Observed coefficient	BootSE	Bootstrapping			
			Bias-corrected 95% CI		Percentile 95% CI	
			Lower	Upper	Lower	Upper
Indirect Effect	0.020	0.010	0.004	0.043	0.003	0.042
Direct Effect	0.055	0.019	0.038	0.113	0.035	0.111
Total Effect	0.075	0.020	0.015	0.093	0.013	0.093

Source: Author's calculations

3.4.4 Robustness Analysis

(1) Replacement of Explained variable

In the previous paper, we chose to construct a customized evaluation system as a variable to measure enterprise performance, and now we choose the method of replacing the explanatory variables to conduct the robustness test. According to the State Council of China's "Enterprise Performance Evaluation Standard Value 2020", the evaluation of listed companies' business performance mainly adopts the financial indicator of return on equity (ROE) as the core measurement basis. Therefore, this paper replaces the explanatory variables with return on equity (ROE) for regression, and the results are shown in Table 7. Whether adding control variables or only controlling the year and individual, they are all significant at the 5% level, effectively supporting Hypothesis 1.

Table 7 Regression results with replacement of explanatory variables

Variables	(1)ROE	(2)ROE
Digital	0.0142**	0.0133**
	(0.0067)	(0.0067)
Size		0.0294**
		(0.0146)
Age		-0.1356
		(0.1566)
Dual		0.0021***
		(0.0007)
Top10		-0.0053
		(0.0115)
Audit		-0.0303**
		(0.0138)
_cons	-0.0002	-0.2279
	(0.0207)	(0.5830)
Year fixed effect	Yes	Yes
Company fixed effect	Yes	Yes
N	1395	1395
adj. R^2	0.4160	0.4195

Standard errors clustered at the firm level are reported in parentheses

Source: Author's calculations

(2) Replacement of Explanatory variable

The digitization word frequency index constructed by text analysis in the previous paper has a certain degree of subjectivity, which may affect the stability of the research conclusions. In order to enhance the reliability of the conclusions, the "Digital Transformation Index" in the CSMAR database is re-selected as a measurement index, which systematically evaluates the six dimensions of strategic foresight, technological innovation, organizational change, environmental suitability, results conversion rate and application breadth. Therefore, this paper replaces the explanatory variables with the digital transformation index for regression, and the results are shown in Table 8. In column (1), when only year and individual fixed effects are introduced, the estimated coefficient of digital transformation level (DTI) reaches 0.5346 at this point, showing a significant positive association. Then, after incorporating multi-dimensional control variables in column (2), the regression coefficient of digital transformation level is 0.3694, which is still statistically significant although the significance level has been reduced. It also effectively supports Hypothesis 1.

Table 8 Regression results of replacing explanatory variables

Variables	(1)FirmPerf	(2)FirmPerf
DTI	0.5346**	0.3694*
	(0.2198)	(0.2151)

Size		-0.0169
		(0.0328)
Age		0.3303**
		(0.1536)
Dual		0.0431*
		(0.0260)
Top10		0.0000
		(0.0016)
Audit		-0.0255
		(0.0321)
_cons	0.9076***	0.3001
	(0.0886)	(0.7625)
Year fixed effect	Yes	Yes
Company fixed effect	Yes	Yes
N	1395	1395
adj. R^2	0.8561	0.7713

Standard errors clustered at the firm level are reported in parentheses

Source: Author's calculations

(3) Alternative Clustering of Standard Errors

To control for the correlation among firms within manufacturing sub-sectors, we conducted a cluster regression after segmenting the manufacturing industry. The results are shown in Table 9. Column (1) presents the results when only annual and individual fixed effects are included. The estimated parameter for the firm's digital transformation level (Digital) is 0.0429, which is statistically significant at the 5% level. Subsequently, in Column (2), a series of control variables were added to further examine the relationship between these two factors. At this stage, the regression coefficient for Digital transformation level remained significant after clustering by manufacturing sub-sector, though the significance level decreased to 10%. This indicates that the heterogeneity within sub-sectors partially weakened the effect, yet the overall direction remained unchanged. This confirms the robustness of Hypothesis 1.

Table 9 Regression results using clustering standard errors

Variables	(1) FirmPerf	(2) FirmPerf
Digital	0.0429**	0.0348*
	(0.0193)	(0.0182)
Size		-0.0248
		(0.0506)
Age		0.2139
		(0.4267)
Dual		0.0519
		(0.0498)
Top10		0.0001

		(0.0019)
Audit		-0.0243
		(0.0509)
_cons	1.0104***	0.7285
	(0.0599)	(1.6574)
Year fixed effect	Yes	Yes
Company fixed effect	Yes	Yes
N	1395	1395
adj. R^2	0.7831	0.7848

Standard errors clustered at the 2-digit industry level are reported in parentheses

Source: Author's calculations

3.4.5 Endogeneity Analysis

Considering potential endogeneity issues such as reverse causality between digital transformation and firm performance, this study adopts an instrumental variable approach for robustness. Following Arellano and Bond (1991) and Chao et al. (2021), we use the one-period lagged digital transformation (l_Digital) and the digital infrastructure level (digfra) as instruments.

For l_Digital, the relevance condition holds because digital transformation is an inertial process where a firm's past digitization heavily correlates with its current level. The exclusion restriction is satisfied because current firm performance cannot retroactively affect prior-year digital decisions, thereby eliminating reverse causality.

For digfra, measured by the text frequency share of "new digital infrastructure" in local government work reports, relevance is achieved because historical regional infrastructure sets the physical and technical foundation for the digital economy. As a leading indicator of IT diffusion, it dictates regional network effects and corporate technology acquisition costs, directly influencing local firms' adoption probability and depth. The exclusion restriction is met because digfra is a macro-level regional variable that does not directly affect individual firms. Moreover, as predetermined historical data, it predates current corporate operations and remains exogenous to current firm-level behaviors.

Table 10 reports the two-stage regression results of the instrumental variables method. First, the first-stage results in Column (1) verify the relevance of the instruments. The coefficient of digital infrastructure (digfra) is significantly positive at the 10% level, and the one-period lagged digital transformation (l_Digital) is highly significant and positive at the 1% level. This establishes a significant positive link between both instruments and the endogenous variable (Digital), meeting the relevance requirement. Second, diagnostic tests confirm that the instruments are valid and reliable. The Kleibergen-Paap LM statistic of 320.126 ($p = 0.0000$) rejects the null hypothesis of underidentification at the 1% level. The Kleibergen-Paap Wald rk F statistic of 1256.70 safely exceeds the Stock-Yogo critical value (19.93) at the 10% bias level, ruling out weak instruments. Additionally, the Hansen J test for the overidentified model yields a p-value of 0.8188, failing to reject the null hypothesis of instrument exogeneity. This confirms compliance with the exclusion restriction and rules out alternative transmission channels. Finally, the second-stage results in Column (2) confirm our core hypothesis. After correcting for endogeneity, the coefficient on the fitted digital transformation (Digital_hat) is

0.0812, remaining highly significant at the 1% level. Thus, even after controlling for two-way fixed effects and addressing reverse causality and omitted variable biases, digital transformation still significantly boosts the performance of listed manufacturing firms, reinforcing the robustness of our baseline findings.

Table 10 Endogeneity Analysis results

Variables	First Stage	Second Stage
	(1)Digital	(2)FirmPerf
Digital_hat		0.0812***
		(0.0166)
digfra	53.1319*	
	(30.6415)	
l_Digital	0.8408***	
	(0.0168)	
Size	0.0352***	0.0190
	(0.0114)	(0.0140)
Age	-0.1013	0.0428
	(0.0621)	(0.0790)
Dual	-0.0787**	-0.1014***
	(0.0329)	(0.0359)
Top10	-0.0002	0.0052***
	(0.0010)	(0.0010)
Audit	-0.0144	-0.1894***
	(0.0639)	(0.0285)
_cons	0.1864	0.9391**
	(0.3177)	(0.4040)
Kleibergen-Paap LM statistic	320.126*** [0.0000]	
Kleibergen-Paap Wald rk F statistic	1256.70 {19.93}	
Hansen J statistic	0.052 [0.8188]	
Year fixed effect	Yes	Yes
Company fixed effect	Yes	Yes
N	1032	1032
adj. R^2	0.8159	0.0610

Standard errors clustered at the firm level are reported in parentheses

Source: Author's calculations

3.4.6 Heterogeneity Analysis

(1) Property Rights Heterogeneity

Since systematic differences exist between state-owned enterprises (SOEs) and non-state-owned enterprises (non-SOEs) regarding their political attributes, strategic positioning, and market environments, such institutional variances may lead to divergent patterns in technology investments and resource access. To explore how ownership characteristics modulate our empirical baseline, we divide the sample into state-controlled and non-state-controlled sub-samples for group regressions. The corresponding empirical estimates are detailed in Table 11.

As shown in Column (1), the estimated coefficient of digital transformation (Digital) is positive and statistically significant for SOEs, whereas it fails to pass the significance test for non-SOEs in Column (2). This divergence can be attributed to two main factors. On the one hand, relying on specialized government funds and policy mandates, SOEs can overcome the substantial financial and technological barriers inherent in large-scale digital upgrades, systematically optimizing their entire supply chains. Conversely, non-SOEs frequently face high financing costs and technological adaptation barriers, forcing them to adopt localized or fragmented digital configurations that fail to yield significant synergistic dividends. On the other hand, digital initiatives within SOEs often carry a degree of policy compliance or political incentives, ensuring continuous capital commitment. In contrast, non-SOEs are highly sensitive to short-term market fluctuations and survival pressures, making them prone to scaling back or interrupting their digital investments under macroeconomic uncertainties. Consequently, technological spillovers in highly competitive markets may erode their early-mover advantages, resulting in an insignificant performance increment. Overall, these findings underscore that the performance-enhancing dividends of corporate digitalization are significantly contingent upon ownership structures.

Table 11 Regression results for ownership heterogeneity

Variables	**FirmPerf**	
	(1)state-owned	**(2)non-state-owned**
Digital	0.0564^{**}	0.0041
	(0.0276)	(0.0207)
Size	-0.0864	0.3215^{***}
	(0.0834)	(0.0734)
Age	0.4162	0.8058
	(0.7904)	(2.8146)
Dual	0.0150	0.0000
	(0.0561)	(0.0339)
Top10	-0.0007	-0.0038
	(0.0039)	(0.0026)
Audit	-0.0607	-0.0144
	(0.0798)	(0.0477)
_cons	2.2154	-1.4331
	(2.3481)	(1.4027)
Year fixed effect	Yes	Yes
Company fixed effect	Yes	Yes
N	400	995
adj. R^2	0.7970	0.8273

Standard errors clustered at the firm level are reported in parentheses

Source: Author's calculations

(2) Regional Heterogeneity

The differentiated characteristics of geographic location significantly moderates the strength of the association between digital transformation and business outcomes. Systematic differences across regions in terms of the degree of digital infrastructure sophistication, the stage of development of economic level, and the maturity of market mechanisms together constitute important contextual factors affecting the effectiveness of technological transformation. In order to examine this spatial heterogeneity in depth, this paper divides the sample firms into three major regions, namely, east, central and west, according to geographic location for group regression, and the results are detailed in Table 12.

The samples in Columns (1), (2), and (3) are the eastern, central, and western firms, respectively, and it can be seen that the positive correlation between the level of digital transformation of the manufacturing firms in the eastern region (Digital) and the organizational effectiveness fails to pass the significance test, for manufacturing enterprises in the central region, the estimated value of digital transformation level (Digital) is 0.1467, which passes the 1% significance test; in contrast, the digitalization parameter of similar enterprises in the western region reaches 0.0827, which is statistically significant at the 10% confidence level. This may be because: the eastern region manufacturing enterprises digital foundation is perfect, technology application is close to the stage of diminishing marginal returns, coupled with the saturation of market-based competition, further investment is difficult to open the performance gap; manufacturing enterprises in the central region are in the policy-driven transformation acceleration period, through the complementary information technology short boards and the introduction of late-breaking technology, significantly releasing the dividends of efficiency; manufacturing enterprises in the western region with a weak digitalization foundation, the early stage The introduction of simple digital tools can quickly improve the efficiency of basic management, resulting in a small increase in short-term performance. However, limited by the technology absorption capacity, it is difficult to deepen the application of technology, and the long-term effect is unstable. Overall, the performance improvement effect of digital transformation is closely related to the stage of regional economic development, the strength of policy support and the technological foundation of enterprises.

Table 12 Regression results of regional heterogeneity

Variables	FirmPerf		
	(1) Eastern	(2) Central	(3) Western
Digital	0.0153	0.1467^{***}	0.0827^{*}
	(0.0179)	(0.0305)	(0.0502)
Size	0.0172	0.2472^{*}	0.0427
	(0.0345)	(0.1468)	(0.0308)
Age	-0.3052	1.8485^{***}	-1.6471
	(0.4405)	(1.3324)	(1.0935)
Dual	0.0663^{**}	0.0482	-0.4589^{***}
	(0.0267)	(0.0875)	(0.1005)
Top10	0.0000	0.0038	0.0071^{***}
	(0.0018)	(0.0043)	(0.0022)
Audit	-0.0210	-0.0340	-0.2330^{**}
	(0.0414)	(0.1061)	(0.1039)

_cons	0.9179	-2.2342	3.6400
	(1.1745)	(3.3469)	(2.4844)
Year fixed effect	Yes	Yes	Yes
Company fixed effect	Yes	Yes	Yes
N	945	255	195
adj. R^2	0.7331	0.8929	0.2229

Standard errors clustered at the firm level are reported in parentheses

Source: Author's calculations

4. Conclusion

4.1 Research Findings

In this paper, A-share manufacturing companies listed in Shanghai and Shenzhen from 2019 to 2023 are selected as research samples, and text mining technology is used to quantify the word frequency of enterprises' digital features, to construct digital transformation evaluation indexes, and to examine the mediating effect of innovation capability. In addition, this paper also analyzes the heterogeneity from the dimensions of property rights and region. Through systematic theoretical discussions and empirical tests, the main research findings are as follows:

First, the empirical results demonstrate a significant, positive association between digital transformation and the performance of manufacturing enterprises. To ensure the reliability of these findings, a series of robustness checks were conducted—including the alternative variable method and the estimation of cluster-robust standard errors—yielding consistently stable results. This underscores that advancing digitalization serves as a potent strategic lever for bolstering the core competitiveness of manufacturing firms.

Second, mechanism analysis reveals that innovation capability plays a critical mediating role in the relationship between digitalization and corporate performance. Specifically, digital transformation effectively catalyzes corporate innovation momentum by enhancing information-processing efficacy and market responsiveness, which subsequently translates into sustained performance advantages.

Finally, heterogeneity analysis indicates that the performance-enhancing effects of digital transformation vary significantly across ownership types and geographic locations. Notably, state-owned enterprises (SOEs) exhibit more pronounced performance gains following technological transformation than non-SOEs, likely due to their distinct institutional advantages, policy support, and robust risk-mitigation capacities. Regionally, the positive impact of digitalization on organizational effectiveness is particularly prominent in the central and western regions. This regional divergence can be explained by the diminishing marginal returns in the eastern region, where the digital infrastructure is already matured, whereas the central and western regions possess greater developmental headroom, leading to more accelerated short-term performance gains.

4.2 Policy Recommendations

4.2.1 From Government Perspective

First, institutionalize tailored policy frameworks and optimized investment sequencing based on empirical baseline efficacy. Consistently mirroring the empirical finding that digital transformation yields significant performance dividends yet varies across firm attributes, government agencies should design differentiated support mechanisms rather than employing a one-size-fits-all approach. These targeted policies must strategically account for corporate lifecycles, ownership structures, and regional characteristics. Crucially, to ensure that more manufacturing firms can successfully unlock the baseline positive performance observed in this study, the government must optimize the sequencing of fiscal interventions; initial-stage subsidies and tax incentives should prioritize foundational digital infrastructure and early-stage exploratory R&D to mitigate early-stage transition frictions. Concurrently, government bodies must maintain high policy agility, dynamically adjusting the policy tool mix and funding sequences in response to technical iterations and empirical market feedback.

Second, construct a multi-tiered governance framework and financial support ecosystems to stabilize transformation returns. While the robust empirical results confirm the strategic value of digitalization, the operational volatilities during the transition demand institutional safeguarding to sustain these performance gains. Government departments should establish cross-industry digital governance standards, encompassing data security, privacy compliance, and risk early-warning systems to mitigate systemic risks that could otherwise jeopardize corporate effectiveness. Concurrently, addressing the underlying financial friction is paramount; by innovating financial support instruments and lowering credit access barriers to match the progressive stages of corporate digitalization, the government can effectively alleviate the funding constraints faced by enterprises, thereby providing a stabilized macro-environment that allows digital inputs to seamlessly translate into tangible performance improvements.

Third, prioritize private manufacturing entities by lowering institutional barriers and fostering public infrastructure. To mitigate the institutional frictions faced by non-public firms, government agencies should deploy a three-pronged enablement system: one, establish specialized programs to assist private enterprises in building industrial data platforms, resolving bottlenecks in data acquisition; two, optimize the institutional environment by streamlining administrative approvals, broadening credit channels, and reducing the institutional costs of technological compliance; and three, accelerate the localized deployment of industrial internet infrastructure while building industry-level public service platforms to minimize entry barriers for small- and medium-sized private firms.

Fourth, formulate differentiated regional strategies to mitigate structural disparities and coordinate resource distribution. In response to geographical variations in digital dividends, a spatially sequenced policy package is required. For the mature eastern regions, the governance focus should shift toward quality-upgrade projects, directing resources toward core bottleneck breakthroughs and high-end manufacturing clusters to leverage industrial synergies. For the central regions, policy continuity must be reinforced to improve cross-chain digital collaboration. For the developing western regions, the state should augment support for the "East Data, West Computing" national initiative, strategically prioritizing the deployment of labor-intensive digital industries—such as data annotation and algorithm training—at pivotal computing hub nodes.

4.2.2 From Enterprise Perspective

First, orchestrate strategic investment sequencing calibrated against ownership and regional heterogeneities. In light of the empirical heterogeneity analysis showing that performance dividends vary significantly by ownership types and geographic locations, manufacturing firms must avoid blindly copying generic digitalization templates. Instead, enterprises—especially non-SOEs with tighter resource constraints—must implement a disciplined, phased investment roadmap. In the initial phase, capital allocation should be strictly sequenced toward low-risk, high-yield operational upgrades and fundamental cloud integration. As digital maturity and cash flows stabilize, firms can progressively escalate investments into advanced frontier technologies like AI and the Industrial Internet, thereby smoothing the digital cost curve against their specific organizational risk-bearing capacities.

Second, prioritize dynamic capability building to unlock the critical mediating path of innovation. Given the empirical evidence that innovation capability serves as a vital mediating mechanism translating digital inputs into corporate performance, manufacturing firms must recognize that technological acquisition alone is insufficient. To successfully activate this mediation channel, enterprises must channel resources into organizational capability building, specifically focusing on data absorptive capacity and market responsiveness. This operational change requires a dual-track approach: externally, firms should establish long-term, industry-academia-research collaborations with universities to build a specialized talent pipeline that fuels corporate R&D; internally, continuous upskilling initiatives must be deployed to elevate workforce digital literacy, ensuring that newly deployed digital tools directly stimulate corporate innovation momentum rather than becoming underutilized assets.

Third, upgrade internal corporate governance and structural systems to sustain baseline empirical returns. To ensure that the statistically significant, positive association between digital transformation and enterprise performance manifests as stable real-world growth, corporate leadership must implement robust internal governance to mitigate operational frictions. Because digitalization is a systemic disruption that fundamentally reshapes workflows, firms need to establish an agile digital governance framework that clearly delineates data ownership, cross-functional responsibilities, and performance metrics. Senior management must break down long-standing institutional silos by constructing cross-departmental coordination platforms that bridge the gap between IT infrastructure and core business operations. By aligning digital governance with internal control systems, manufacturing firms can abbreviate the structural adaptation period, minimize transition risks, and effectively convert digital investments into sustained financial gains.

Acknowledgment

This paper is supported by “the Fundamental Research Funds for the Central Universities NO.ND2025001”and “Jiangsu Provincial Social Sciences Applied Excellence Project (Special Research on Xi Jinping Thought on Ecological Civilization) NO.STA-17”.

References

Al Khatib, A. W. (2024).The determinants of export performance in the digital transformation era: Empirical evidence from manufacturing firms.*International Journal of Emerging Markets*,19(10),2597-2622. https://doi.org/10.1108/ijoem-08-2022-1223

Andrew F. Hayes. (2009). Beyond Baron and Kenny: Statistical Mediation Analysis in the New Millennium.*Communication Monographs*,76(4),408-420. https://doi.org/10.1080/03637750903310360

Angelopoulos, S., Bendoly, E., Fransoo, J., Hoberg, K., Ou, C., & Tenhiälä, A. (2026).Digital transformation in operations management: Fundamental change through agency reversal. *Journal of Operations Management*,69(6),876-889. https://doi.org/10.1002/joom.1271

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte carlo evidence and an application to employment equations.*The Review of Economic Studies*, 58(2), 277-297 https://doi.org/10.2307/2297968

Bag, S., Shivam, G., Ajay, K., & Uthayasankar, S. (2021).An integrated artificial intelligence framework for knowledge creation and B2B marketing rational decision making for imp roving firm performance.*Industrial Marketing Management*,92,178–189. https://doi.org/10.1016/j.indmarman.2020.12.001

Binsaeed, R. H., Grigorescu, A., Yousaf, Z., Condrea, E., & Nassani, A. A. (2023).Leading role of big data analytic capability in innovation performance: Role of organizational readiness and digital orientation.*Systems*,11(6),Article 284.https://doi.org/10.3390/systems11060284

Bughin, J. (2023).Does artificial intelligence kill employment growth: The missing link of corporate AI posture.*Frontiers in Artificial Intelligence*,6,Article 1239466.https://doi.org/10.3389/frai.2023.1239466

Buhaya, M. I., & Metwally, A. B. M. (2024).The interplay between digital technologies and sustainable performance: Does lean manufacturing matter?*Sustainability*,16(22),Article 10002. https://doi.org/10.3390/su162210002

Cen, J., & Chen, L. (2019). Dual innovation rhythm, internal coordination, and enterprise performance.*Management Review*,31(1),101–112,146. https://doi.org/10.14120/j.cnki.cn11-5057/f.2019.01.010 (in Chinese)

Chao, X. J., Lian, Y. M., & Luo, L. K. (2021). The impact of new digital infrastructure on the high-quality development of manufacturing.*Finance and Trade Research*,32(10),1-13. https://doi.org/10.19337/j.cnki.34-1093/f.2021.10.001 (in Chinese)

Chen, C., Zhu, L., Zhong, H., & et al. (2019). Innovation research on digital survival management practices of Chinese enterprises.*Journal of Management Sciences in China*,22(10),1-8. (in Chinese)

Chen, Y., Hu, W., & Wu, Z. (2020). Construction and evaluation method of performance evaluation index system for Baijiu enterprises: An improved TOPSIS model based on BSC and entropy weight.*Journal of Sichuan University of Science & Engineering (Social Sciences Edition)*,35(5),68-87. (in Chinese)

Dalenogare, L. S., Benitez, G. B., Ayala, N. F., & Frank, A. G. (2018).The expected contribution of Industry 4.0 technologies for industrial performance.*International Journal of Production Economics*,204,383-394. https://doi.org/10.1016/j.ijpe.2018.08.019

Fortier, J., Gamache, S., & Fonrouge, C. (2025).Integrating sustainable performance into the digital maturity models for SMEs in manufacturing. *Applied Sciences*,15(7),Article 4041. https://doi.org/10.3390/app15074041

Horváth, D., & Szabó, R. Z. (2019).Driving forces and barriers of Industry 4.0: Do multinational and small and medium-sized companies have equal opportunities?*Technological Forecasting and Social Change*,146,119-132. https://doi.org/10.1016/j.techfore.2019.05.021

Hu, Y., Wei, H., & Zhu, Y.(2024).The impact of digital transformation on enterprise performance: The mediating effect of deleveraging.*Soft Science*,38(12),101-108. https://doi.org/10.13956/j.ss.1001-8409.2024.12.13 (in Chinese)

Khin, S., & Ho, T. C. F. (2019).Digital technology, digital capability and organizational performance. *International Journal of Innovation Science*,11(2),177-195. https://doi.org/10.1108/IJIS-08-2018-0083

Li, C. T., Yan, X. W., Song, M., & Yang, W. (2020). FinTech and corporate innovation: Evidence from NEEQ-listed companies.*China Industrial Economics*, (1),81–98.https://doi.org/10.19581/j.cnki.ciejournal.2020.01.006(in Chinese)

Li, L., Huang, G., & Yang, S. (2024).The synergistic effect of digitalization and servitization on manufacturing enterprise performance: A fuzzy-set qualitative comparative analysis. *Nankai Business Review*,27(4),197-208(in Chinese)

Li, Q., Li, Y., Zhang, Y., & et al. (2023).Information spillover effects of enterprise digital transformation: Empirical evidence from a supply chain perspective.*China Industrial Economics*,(7),142-159. https://doi.org/10.19581/j.cnki.ciejournal.2023.07.008 (in Chinese)

Lima, M. d. R. F., Franco, C. W., & Benitez, G. B. (2025).Performance returns from aligning front-end digital technologies and Just-in-Time practices: Empirical findings from the Brazilian manufacturing industry.*The International Journal of Logistics Management*,36(5),1463-1494. https://doi.org/10.1108/IJLM-02-2024-0127

Lin, X., & Wu, D. (2021). Blockchain technology and enterprise performance: The moderating role of corporate governance structure.*Management Review*,33(11),341-352. https://doi.org/10.14120/j.cnki.cn11-5057/f.2021.11.024 (in Chinese)

Ling, R. Z., Pan, A. L., & Li, B. (2021). Can supply chain finance improve the innovation level of enterprises?*Journal of Finance and Economics*,47(2),64-78. https://doi.org/10.16538/j.cnki.jfe.20200816.201 (in Chinese)

Ma, H., & Wang, C. (2025).Are digital capabilities always beneficial? A meta-analysis of the relationship between digital capabilities and enterprise performance.*Nankai Business Review*,28(6),4-15(in Chinese)

Orero Blat, M., Palacios Marqués, D., Leal Rodríguez, A. L., & Ferraris, A. (2024).Beyond digital transformation: A multi-mixed methods study on big data analytics capabilities and innovation in enhancing organizational performance.*Review of Managerial Science*,19(2),1 – 37. https://doi.org/10.1007/S11846-024-00768-8

Qi, Y., & Cai, C. (2020).Multiple impacts of digitalization on manufacturing enterprise performance and their underlying mechanisms.*Study & Exploration*, (7),108-119(in Chinese)

Smith, N. D., Hovanski, Y., Tenny, J., & Bergner, S. (2024).Digital performance management: An evaluation of manufacturing performance management and measurement strategies in an Industry 4.0 context.*Machines*,12(8),Article 555. https://doi.org/10.3390/machines12080555

Sun, H., & Wang, H. (2017). Government subsidies, R&D investment, and enterprise innovation performance: An empirical study based on high-tech enterprises on the Growth Enterprise Market.*Science and Technology Management Research*,37(12),111-116(in Chinese)

Turkcan H.(2025).How to improve financial performance through sustainable manufacturing practices? The roles of green product innovation and digital transformation.*Journal of Manufacturing Technology Management*,36(3),577-596. https://doi.org/10.1108/JMTM-03-2024-0112

Turkcan, H., Imamoglu, S. Z., Ince, H., & Erat, S. (2025).Digital capabilities and circular economy practices to enhance environmental and economic performance: The role of digital technology – environmental strategy alignment.*Corporate Social Responsibility and Environmental Management*,32(4),5069-5087. https://doi.org/10.1002/CSR.3230

Vial, G.(2019).Understanding digital transformation: A review and a research agenda.*Journal of Strategic Information Systems*,28(2),118-144. https://doi.org/10.1016/j.jsis.2019.01.003

Wang, Q., Wang, C., & Liu, Y. (2020).The mechanism of retail digital transformation from the perspective of digital capabilities and value creation capabilities: A multiple-case study of new retail.*R&D Management*,32(6),50-65.https://doi.org/10.13581/j.cnki.rdm.20191843(in Chinese)

Wu, F., Hu, H., Lin, H., & Ren, X. (2021). Enterprise digital transformation and capital market performance: Empirical evidence from stock liquidity.*Management World*,37(7),130-144,10. https://doi.org/10.19744/j.cnki.11-1235/f.2021.0097 (in Chinese)

Wu, H., He, X., & Deng, H. (2024).Digital transformation, market power, and enterprise economic performance.*Industrial Economics Research*,(5),28-43.https://doi.org/10.13269/j.cnki.ier.2024.05.002(in Chinese)

Yang, D., Chen, C., & Yang, P. (2023). Digitalization degree, ambidextrous innovation, and enterprise performance.*Statistics & Decision*,39(19),167-172. https://doi.org/10.13546/j.cnki.tjyjc.2023.19.031 (in Chinese)

Ye, C., Qiu, L., & Zhang, L. (2016). Corporate governance structure, internal control quality, and corporate financial performance.*Auditing Research*, (2),104-112(in Chinese)

Yu, D., Chen, H., & Zhang, H. (2024).Digital transformation, servitization integration, and performance improvement of manufacturing enterprises: The moderating effect of economic policy uncertainty.*Finance and Trade Research*,35(4),1-14,56.https://doi.org/10.19337/j.cnki.34-1093/f.2024.04.001(in Chinese)

Yuan, C., Xiao, T., Geng, C., & et al. (2021).Digital transformation and enterprise division of labor: Specialization or vertical integration.*China Industrial Economics*,(9),137-155. https://doi.org/10.19581/j.cnki.ciejournal.2021.09.007 (in Chinese)

Zhai, Y., Jiang, M., & Wang, W. (2021).Theoretical interpretation and operational mechanisms of digital transformation in China.*E-Government*,(6),67-84.https://doi.org/10.16582/j.cnki.dzzw.2021.06.007(in Chinese)

Zhang, H., & Gu, X. (2023).Digital capabilities, open innovation, and enterprise performance: The moderating effect of innovation appropriability.*Science of Science and Management of S.&.T.*,44(6),132-149. https://doi.org/10.20201/j.cnki.ssstm.2023.06.009 (in Chinese)