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When Does Digital Transformation Pay Off? Cost Channels and Heterogeneity in Chinese Manufacturing Firms

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Abstract: Digital transformation serves as a key driver of better firm financial performance and a critical enabler of high-quality economic and social development. Using a panel dataset of Chinese A-share listed manufacturing firms over the 2011–2022 period, this study empirically examines how digital transformation affects firm financial performance, along with its transmission mechanisms and heterogeneous effects. We find that digital transformation significantly improves the financial performance of manufacturing enterprises. Mechanism tests show that digital transformation enhances performance by reducing transaction costs, while the mediating channel through production costs is not supported. Heterogeneity analysis further indicates that the positive performance effect of digital transformation is more pronounced among state-owned enterprises and mature firms. Our findings enrich the literature on digital transformation and firm performance, and provide empirical implications for corporate digital practices and public policies aimed at high-quality development.

Keywords: Digital Transformation; Financial Performance; Transaction Costs; Production Costs; Manufacturing

Introduction

Amid mounting economic pressures and shifting market demands, digital transformation has emerged as a defining force reshaping the global manufacturing landscape. By positioning data as a core factor of production, it reconfigures traditional inputs of capital and labor and fundamentally redefines the logic of value creation[1][2]. As a pillar of global economic growth, the manufacturing sector stands at the forefront of this paradigm shift. Digital technologies are not only shifting operational models from capital-driven to data-driven but are also enabling a deep integration of virtual and physical networks. This integration breaks down the rigid structures of traditional industry, unlocking new efficiency gains[3][4]. Consequently, the profound impact of digital transformation on manufacturing competitiveness and resource allocation efficiency has made it a central focus for both practitioners and scholars[5][6].

At the heart of this transformation, however, lies a persistent debate: does digital transformation actually enhance the financial performance of manufacturing firms? Consensus remains elusive, as theoretical and empirical perspectives remain sharply divided. On one hand, digital transformation is often framed as a key driver of productivity growth—by reducing information asymmetry, optimizing resource allocation, and fostering innovation and cost reduction, it promises to enhance total factor productivity (TFP) and reshape profit mechanisms[7][8]. On the other hand, concerns over a "productivity paradox" endure. Substantial adjustment costs—such as those related to workforce training, infrastructure investment, and organizational

restructuring—along with potential mismatches between technology adoption and organizational capabilities, may delay or even negate gains in performance[3][9].

This unresolved debate highlights two critical questions that warrant further investigation. First, the theoretical underpinnings of how digital transformation influences financial performance remain inadequately developed. Existing studies often focus on estimating its net effect, yet they seldom disentangle the specific economic channels—such as improvements in resource allocation efficiency, reduction in transaction costs, and mitigation of operational risks—that ultimately drive financial outcomes (Chen et al., 2021)[10]. Second, the impact of digital transformation likely varies significantly across firms with different resource endowments and under different institutional conditions. Current research offers limited insight into which firms stand to benefit most.

Addressing these questions is both an academic necessity and a practical imperative. As digital transformation becomes widespread, manufacturing firms require empirically grounded strategies to maximize returns on their digital investments. This study therefore seeks to answer: (1) Does digital transformation improve the financial performance of manufacturing firms as theory suggests? (2) What are the key economic mechanisms through which this relationship operates? (3) How do these effects vary across heterogeneous firms? By answering these questions, this research aims to enrich the literature on the digital economy and offer actionable insights to help firms tailor their digital strategies based on their specific contexts.

1.Theoretical analysis and research hypothesis

1.1 The Effect of Digital Transformation on the Financial Performance of Manufacturing Firms

In the digital transformation of manufacturing, digital technologies reshape core components of a firm's value chain, driving gains in operational efficiency and transformative shifts in value creation models—thereby exerting a systemic influence on corporate financial performance. Specifically, at the operational level, these technologies enable deep synergy and a closed data loop across R&D, production, and sales functions. Technologies rooted in machine learning and predictive analytics markedly optimize product portfolio decisions and R&D resource allocation, shortening innovation cycles and elevating innovative outpu[11][12]. Meanwhile, the Internet of Things (IoT) and real-time data analytics support flexible, intelligent scheduling of production processes, reducing manufacturing costs and boosting asset utilization[13]. On the sales and marketing front, leveraging big data on consumer behavior and intelligent algorithms, firms achieve precise demand insight, personalized recommendations, and dynamic pricing, which in turn lift sales conversion rates and customer lifetime value[14].

Furthermore, digital transformation propels manufacturing firms to evolve toward platform-based, ecosystem-oriented organizational forms, thereby reshaping their profit underpinnings. Digital platforms facilitate the integration of internal and external innovation resources and foster open innovation, allowing firms to respond more agilely to market changes and seize emerging value opportunities[15]. At the same time, the development of user-participatory value co-creation systems—including demand co-creation, process visibility, and closed feedback loops—not only strengthens customer stickiness but also enables continuous refinement of product and service portfolios. This unlocks new revenue streams and builds sustainable competitive advantages for firms[16]. This inward-outward digital restructuring collectively underpins improvements in a firm's profitability, operational efficiency, and market value. Accordingly, this paper formulates the following hypothesis:

H1: Digital transformation in manufacturing has a positive facilitating effect on corporate financial performance.

1.2 Underlying Mechanisms Through Which Digital Transformation Affects the Financial Performance of Manufacturing Firms

Digital technologies reshape information transmission and contractual enforcement, thereby systematically reducing transaction costs for manufacturing firms. On the one hand, comprehensive real-time data aggregation and sharing break down traditional information barriers between supply and demand: big data analytics allows firms to accurately capture heterogeneous consumer demand and feed it back to production in real time, while digital platforms deliver transparent information on supplier qualifications and product specifications, substantially lowering search costs and opportunistic risks driven by information asymmetry (Williamson, 2020; Tang et al., 2022)[18][19]. On the other hand, smart contracts and digital governance redefine the contractual enforcement environment: automated performance terms cut manual monitoring costs,

and cross-organizational digital trust networks reduce the marginal cost of enforcing contractual obligations (Wu et al., 2022; Liu et al., 2024)[15][20].

Digital transformation further curbs implicit transaction costs by strengthening internal and external coordination. Externally, digital cross-organizational networks speed up supply-demand matching and reduce adaptive adjustment costs caused by demand fluctuations)[21][17]. Internally, AI-driven decision support systems integrate market, supply chain, and production data, improving coordination across purchasing, sales, and production units and lowering information losses and bargaining costs in internal governance (Brynjolfsson & Mitchell, 2021)[22]. Taken together, by alleviating information and contractual frictions, digital transformation redefines the transaction efficiency frontier for manufacturing firms and provides a cost foundation for stronger financial performance. We therefore propose the following hypothesis:

H2: Digital transformation significantly improves the financial performance of manufacturing firms by reducing transaction costs.

Digital technologies enable a structural reduction in production costs for manufacturing firms by facilitating precise supply-demand matching and optimizing the allocation of production factors. On the one hand, data-driven supply-demand visibility removes spatial separation and information lags between production and consumption. Using IoT and big data analytics, firms capture heterogeneous consumer demand in real time, and precision production cuts resource waste and inventory holding costs associated with traditional mass production[3][23]. On the other hand, digital technologies support the efficient reconfiguration of production factors. Specifically, industrial internet platforms enable dynamic cross-process scheduling of equipment, labor, and other inputs, while AI algorithms refine production scheduling to raise the overall utilization efficiency of production factors.

Digital transformation further unlocks cost-saving potential by reshaping production models. The modular production paradigm enabled by digital technologies supports efficient R&D and manufacturing of diversified derivatives using standardized components. This expands the boundaries of economies of scope and reduces both R&D and production costs through component commonality [24][25]. Critically, the widespread adoption of flexible manufacturing systems allows seamless switching between large-scale, low-variety production and small-batch, high-variety production, effectively alleviating overcapacity or capacity shortages inherent in traditional manufacturing. This threefold improvement—precision production, flexible capacity, and intelligent operations—systematically strengthens profitability by lowering unit marginal costs and improving fixed cost allocation. We therefore propose the following hypothesis:

H3: Digital transformation significantly enhances the financial performance of manufacturing firms by reducing production costs.

2.Research design

2.1 Model design

2.1.1 baseline model

In order to test the impact of digital economy on financial performance in the manufacturing sector, this study constructs baseline panel fixed-effect model as in eq. (1):

$$ROE_{i,t} = \alpha_0 + \alpha_1 DT_{i,t} + \alpha_2 Age_{i,t} + \alpha_3 Lev_{i,t} + \alpha_4 Board_{i,t} + \alpha_5 Cash_{i,t} + \alpha_6 Growth_{i,t}$$
$$+ \alpha_7 Indep_{i,t} + \sum Owner + \sum Year + \sum Province + \varepsilon_{i,t} \tag{1}$$

where ROE is the dependent variable measuring corporate financial performance, DT is the independent variable representing digital transformation, and ε_{ijt} denotes the error term. The model also controls for firm ownership (Owner), as well as year and province fixed effects, with all remaining variables included as additional controls.

2.1.2 mediation effects model

This study examines the underlying mechanisms linking digital transformation and corporate financial performance through two key channels: transaction costs and production costs:

$$Transaction / \text{Cos} t = \beta_0 + \beta_1 DT_{i,t} + \beta_2 Controls + \sum Owner + \sum Year + \sum Province + \varepsilon_{i,t} \tag{2}$$

$$ROE_{i,t} = \lambda_0 + \lambda_1 DT_{i,t} + \lambda_2 Controls + \sum Owner + \sum Year + \sum Province + \varepsilon_{i,t} \tag{3}$$

2.2 variables Selection

2.2.1 Explained variables

Corporate Financial Performance (ROE). Prior literature commonly measures corporate financial performance using accounting metrics drawn from listed firms' annual reports, which reflect profitability, operational efficiency, and solvency—including return on equity (ROE), return on assets (ROA), and earnings per share (EPS). Following the mainstream approach, this study adopt return on equity (ROE) as our baseline dependent variable for financial performance. For robustness tests, we employ two alternative proxies: return on assets (ROA), which captures overall asset-based profitability, and earnings per share (EPS), which gauges shareholder-level returns.

2.2.2 Explanatory variable

Digital Transformation (DT). Measuring firm-level digital transformation poses a notable challenge in the existing literature. We follow the measurement framework developed by Hu &Zhong (2023)[26]. First, consistent with Wu et al. (2021)[27], we construct a comprehensive digital lexicon spanning five categories: artificial intelligence, big data, cloud computing, blockchain, and digital technology application. Second, using the Python "jieba" module for word segmentation, we perform textual analysis and word frequency counting on listed firms' annual reports. Finally, we aggregate the frequencies of all digital-related keywords for each firm-year to obtain a total count, which serves as our measure of digital transformation intensity.

2.2.3 Mechanism Variables

This study identifies transaction costs (Transaction) and production costs (Manufacture) as the mediating variables. Following Chang（2019）[28], we proxy market transaction costs using the sales expense ratio, defined as the ratio of sales expenses to operating revenue. In addition, the production cost ratio—calculated as the ratio of production costs to a firm's operating revenue—captures the firm's production cost level.

2.2.4 Control variable

To account for other factors influencing corporate financial performance, we include the following control variables. Firm age (Age) is computed as the natural logarithm of the number of years since the firm's establishment plus one. Leverage (Lev) is defined as the ratio of total liabilities to total assets. Board size (Board) is measured as the natural logarithm of the number of directors. Cash flow (Cash) reflects operating conditions and is proxied by the ratio of operating cash flows. Firm growth (Growth) is measured using Tobin's Q, a widely adopted metric for growth potential. Board independence (Indep) is defined as the share of independent directors on the board. The descriptive statistical results of the data involved in the paper are shown in Table 1.

Table 1 Descriptive statistics of variables

Variables sample	Sample size	Mean	Standard deviation	Minimum value	Maximum value
ROE	16,400	0.0650	0.122	-0.578	0.352
DT	16,400	2.850	1.142	0	5.613
Transaction	16,400	0.712	0.170	0.172	0.992
Manufacture	16,400	0.0813	0.0965	0.00204	0.499
Age	16,400	10.64	7.105	2	27
Lev	16,400	0.395	0.190	0.0559	0.863
Board	16,400	8.399	1.508	5	13
Growth	16,400	2.156	1.350	0.880	8.622
Cash	16,400	0.961	0.184	0.451	1.435
Indep	16,400	0.381	0.0654	0.250	0.600

2.3 Data sources

This study draws on a sample of 2,062 manufacturing firms listed on China's A-share market from 2012 to 2022. We exclude firms under special treatment (ST or *ST), those with missing data, and firms with less than five years of continuous operation. The final unbalanced panel consists of 16,400 firm-year observations. To mitigate the influence of outliers, all continuous variables are winsorized at the 1st and 99th percentiles. Data processing is performed using STATA 17.0. Firm-level digital transformation metrics are sourced from the Mark Data Network, while financial data are obtained from the China Stock Market & Accounting Research (CSMAR) Database.

3.Empirical results and analysis

3.1 Baseline regression analysis

Table 2 presents the regression results examining the impact of digital transformation on the financial performance of manufacturing firms. Column (1) reports estimates with only year, province, and industry fixed effects, while column (2) adds firm-level controls. The coefficient on digital transformation (DT) is positive and statistically significant at the 1% level, supporting Hypothesis H1 that digital transformation improves firm financial performance.

A plausible mechanism is that deeper digital transformation enables business model innovation, allowing firms to leverage digital platforms for cross-functional integration. This enhances resource allocation, meets individualized consumer needs, and improves supply–demand coordination, thereby boosting financial outcomes.

To mitigate potential endogeneity, column (3) uses the one-period lag of DT (L.DT). The significantly positive coefficient suggests that the effect of digital transformation on financial performance persists over time, further confirming the reliability of H1. This indicates that digital transformation provides sustained financial benefits, supporting its role as a durable strategic upgrade for sustainable firm development.

Table 2 Regression results of the benchmark model

Variables	（1）	（2）	（3）
	ROE		
DT	0.006***	0.008***	
	(5.81)	(8.80)	
L.DT			0.005***
			(4.28)
Age		-0.000	0.000**
		(-0.14)	(2.49)
Lev		-0.150***	-0.152***
		(-18.18)	(-16.29)
Board		0.007***	0.008***
		(9.44)	(9.70)
Growth		0.009***	0.010***
		(8.46)	(8.51)
Cash		-0.052***	-0.054***
		(-8.56)	(-8.02)
Indep		0.054***	0.058***
		(3.33)	(3.29)
Owner/Year/Province	YES	YES	YES
Constant	0.047***	0.065***	0.025
	(8.96)	(4.57)	(1.52)
N	16,400	16,400	13,447
R^2	0.028	0.101	0.101

Note: ***, ** and * represent the significance level of 1%, 5% and 10% respectively; The values in the brackets are t-statistics, the same below.

3.2 Robustness check

3.1.1 Excluding firm-year observations from atypical periods

To address potential confounding effects from extreme shocks, we first exclude observations from 2020, when the COVID-19 pandemic severely disrupted national economic activity and introduced heightened volatility in the financial performance of manufacturing firms. As shown in Table 3, the coefficient on digital transformation remains significantly positive at the 1% level, confirming that the performance-enhancing effect of digital transformation is robust to this sample restriction. We further conduct regressions using the first-order lag of digital transformation (L.DT). As reported in Column (2), the coefficient on L.DT is significantly positive at the 1% level, and the lagged effect of digital transformation persists even after excluding 2022—a year of potential structural volatility. These results collectively support Hypothesis H1 and remain qualitatively unchanged.

Table 3 Robustness test results 1

Variables	（1）	（2）
	ROE	
DT	0.008***	
	(8.13)	
L.DT		0.004***
		(3.65)
Owner/Year/Province	YES	YES
Constant	0.065***	0.034*
	(4.26)	(1.76)
N	14,289	9,735
R^2	0.099	0.096

3.1.2 Substitute variables

To further verify the robustness of our baseline findings, we substitute the primary measure of financial performance with two alternative variables: return on assets (ROA) and earnings per share (EPS). As shown in Table 4, the coefficient on digital transformation remains positive and statistically significant at the 1% level when ROA is used as the dependent variable (column 1) and similarly when EPS is employed (column 3). These results confirm that the positive effect of digital transformation on firm performance is not sensitive to the choice of performance metric, thereby strongly supporting Hypothesis H1.

We also re-examine these specifications using the one-period lag of digital transformation (L.DT). Columns (2) and (4) indicate that the lagged effect remains positive and significant for both ROA and EPS, suggesting that the positive impact persists over time. The consistency of these findings across alternative performance measures reinforces the reliability of our main conclusion.

Table 4 Robustness test results 2

Variables	(1)	(2)	(3)	(4)
	ROA		EPS	
DT	0.003***		0.039***	
	(7.25)		(7.95)	
L.DT		0.001***		0.023***
		(2.85)		(4.31)
Owner/Year/Province	YES	YES	YES	YES

Variables	(1)	(2)	(3)	(4)
	ROA		EPS	
Constant	0.050***	0.026***	-0.220***	-0.524***
	(7.75)	(3.45)	(-2.91)	(-6.07)
N	16,400	13,447	16,400	13,447
R^2	0.200	0.195	0.092	0.084

3.3 Channel analysis

Table 5 presents the results of the mechanism tests for transaction costs and production costs. As shown in Column (1), the coefficient of digital transformation (DT) on transaction costs is significantly negative at the 1% level, indicating that transaction costs decline significantly as manufacturing firms deepen their digital transformation. Column (2) shows that the coefficient of transaction costs (Transaction) on financial performance is −0.216 and highly significant, confirming that digital transformation enhances financial performance by reducing transaction costs. Hypothesis H2 is therefore supported.

This finding aligns with the transaction cost framework in new institutional economics and reflects the real-world operating features of China's manufacturing sector. Traditional manufacturing is characterized by long industrial chains, geographically dispersed supply chains, and persistent information silos between firms, suppliers, and customers. High information asymmetry not only raises ex ante transaction costs—such as search costs, partner screening, and negotiation expenses—but also induces opportunism and moral hazard, which in turn inflate ex post costs of monitoring, contract enforcement, and dispute resolution. Digital transformation mitigates these frictions by enabling real-time data aggregation, cross-organizational information sharing, and end-to-end visibility across transactions. On the one hand, big data analytics and digital transaction platforms sharply reduce search and matching costs and alleviate adverse selection stemming from information asymmetry. On the other hand, digital contracting, online performance tracking, and integrated supply chain governance strengthen behavioral discipline among trading partners, lower monitoring and enforcement costs, and contain opportunistic behavior amid external market uncertainty. By delivering a comprehensive reduction in search, contracting, monitoring, and enforcement costs, digital transformation shifts manufacturing from fragmented, inefficient traditional transactions toward a more integrated and coordinated digital ecosystem. The resulting cost savings ultimately translate into stronger financial performance.

Column (3) shows that the coefficients of digital transformation (DT) and production costs (Manufacture) are significantly positive at the 1% level. In Column (4), the regression coefficient of production costs (Manufacture) on financial performance is insignificant, indicating that production costs do not act as a mediating channel. For robustness, we conduct the Sobel test: the Z-statistic for production costs is −1.86 (insignificant), and the bias-corrected confidence interval from the Bootstrap test includes zero, confirming that the mediating effect is not valid. These results imply that digital transformation does not reduce corporate production costs and thus fails to improve financial performance, meaning Hypothesis H3 is not supported.

One plausible explanation lies in four interrelated economic and institutional constraints embedded in China's manufacturing sector, consistent with the digital transformation literature [22][27][29]. First, short-term cost crowding-out dominates potential efficiency gains: most manufacturing firms in our sample are at an early stage of digitalization, with heavy upfront investments in hardware, software, and workforce training that directly raise short-term production costs, outweighing any modest efficiency improvements. Second, critical complementary assets are missing[30]: low digital maturity means firms lack synchronized investment in organizational restructuring, skilled digital labor, and cross-firm supply chain integration. Without these complements, technologies such as modular production, flexible manufacturing, and real-time supply–demand visibility cannot be fully deployed, leaving traditional extensive growth models intact. Third, scale and network thresholds are unmet[31]: many manufacturers remain small-scale with fragmented digital systems, failing to reach the critical mass needed for network effects that drive large-scale cost reduction. Fourth, path dependence in production models persists[32]: decades of extensive, capital-intensive manufacturing have created institutional inertia, with most firms only adopting superficial digital tools rather than reshaping core production processes. As a result, digitalization remains limited to partial automation rather

than systemic optimization of resource allocation, making it unable to mitigate cost pressures or deliver sustained production efficiency gains in the short to medium run.

Table 5 Channel analysis results 1

Variables	(1)	(2)	(3)	(4)
	Transaction	ROE	Manufacture	ROE
DT	-0.012***	0.009***	0.004***	0.009***
	(-10.90)	(6.76)	(6.30)	(9.47)
Transaction		-0.216***		
		(-35.12)		
Manufacture				-0.010
				(-0.97)
Owner/Year/Province	YES	YES	YES	YES
Constant	0.865***	0.252***	-0.058***	0.064***
	(54.80)	(18.62)	(-5.88)	(4.98)
N	16,400	16,400	16391	16391
R^2	0.31	0.18	0.15	0.10

Table 6 Channel analysis results 2

	Transaction	Manufacture
Sobel test	0.0031（z=13.92***）	-0.00008（z=-1.86）
Goodman test1	0.0031（z=13.92***）	-0.00008（z=-1.84）
Goodmantest2	0.0031（z=13.93***）	-0.00008（z=-1.88）
mediation effect coefficient	0.0031（z=13.92***）	-0.00008（z=-1.86）
direct effect coefficient	0.0053（z=6.74***）	0.0091(z=10.52***)
total effect coefficient	0.0084（z=10.44***）	0.0090(z=10.44***)
mediated proportion	0.3704	-0.0091

3.4 Heterogeneity analysis

This study examines whether the effect of digital transformation on manufacturing firms' financial performance varies with firm ownership and life cycle stage. First, we classify Chinese listed firms into two groups based on ownership type: state-owned enterprises (SOEs) and non-state-owned enterprises (non-SOEs). Columns (1) and (2) of Table 5-8 indicate that digital transformation is significantly positively associated with financial performance among SOEs. One plausible explanation is that SOE executives bear considerable responsibility for policy implementation, employment stability, and social welfare objectives. Amid strong national promotion of digital transformation, SOEs therefore exhibit greater policy alignment and stronger incentives to proactively implement digital initiatives.

Second, we split the sample into growth firms and mature firms using a firm-age threshold of 10 years. Columns (3) and (4) of Table 5-8 show that digital transformation has a substantially stronger positive effect on financial performance for mature firms. Mature firms typically benefit from longer operating histories, richer resource endowments, and stronger brand reputation. Since customers tend to favor established firms over younger growth-stage entrants, this demand-side advantage reinforces the performance gains from digital transformation among mature manufacturing firms.

Table 7 Heterogeneity analysis results

Variables	(1)	(2)	(3)	(4)
	non-SOEs	SOEs	Growth Stage	Mature Stage
	ROE			
DT	0.013***	0.006***	0.004***	0.015***
	(7.47)	(5.33)	(3.66)	(9.28)
Owner/Year/Province	YES	YES	YES	YES
Constant	0.080***	0.048***	0.053***	0.068***
	(3.26)	(2.80)	(3.17)	(3.06)
N	4,720	11,680	8,669	7,731
R^2	0.168	0.110	0.126	0.118

4.Conclusion and implications

4.1 research conclusion

In recent years, with the rapid advancement of advanced technologies including big data, blockchain, and cloud computing, digital transformation has emerged as a pivotal driver of industrial upgrading and high-quality development for traditional real economy firms. This study employs a sample of 16,400 firm-year observations from 2,062 manufacturing listed companies on China's A-share market over the 2012–2022 period to examine the impact of digital transformation on manufacturing firms' financial performance and the underlying mechanisms of this relationship. Key findings are as follows: (1) Manufacturing firms' digital transformation exerts a significantly positive effect on their financial performance, and the digital economy exhibits a notable lagged impact on firms' financial outcomes. (2) The advancement of digital technologies further mitigates the constraining effect of transaction costs on the financial performance of manufacturing firms. (3) The impact of digital transformation on manufacturing firms' financial performance is heterogeneous: it yields a weaker positive effect for non-state-owned enterprises and firms in the growth stage, whereas a substantially stronger positive effect is observed for state-owned enterprises and mature firms.

4.2 Practical Implications

4.2.1 Continuous Policy Guidance and Support for Deepening Digital Transformation

Policy-driven deep digital transformation of manufacturing firms is a pivotal measure to elevate the sector's overall financial performance. On one hand, governments should strengthen strategic advocacy and exemplary demonstration—by releasing industry white papers on digital transformation and showcasing successful practices of benchmark firms—to foster a long-term mindset among corporate decision-makers, break their cognitive reliance on traditional resource-driven growth, and deepen their understanding of digitalization's core role in driving cost reduction, efficiency gains, and value upgrading. On the other hand, policymakers need to scale up targeted support to address pain points in corporate transformation such as technological incompatibility and financial constraints: establish special subsidies for digital transformation, build public digital technology service platforms, and incentivize firms to leverage mature technologies including the Internet of Things and big data to restructure an integrated management system for production, procurement, and sales. This shift from extensive to refined production models, enabled by breaking down data silos, optimizing resource allocation, and cutting operational costs, empowers manufacturing firms to achieve concurrent improvements in financial performance and long-term firm value.

4.2.2 Strengthening the Development of Data Processing and Analytics Capabilities

Governments should take the lead in formulating unified data governance standards for the manufacturing sector, building cross-entity public data sharing platforms, and opening up non-confidential industry foundational data to reduce firms' transaction costs of data acquisition, verification, and interoperability at the source. They should also establish special funding for data technology applications, providing targeted support for firms to deploy practical data analytics tools for core

scenarios including production scheduling and supply chain collaboration. Data-driven evidence-based decision-making optimizes resource allocation, cutting explicit production costs such as material waste and capacity redundancy. Firms must integrate data capability development into daily operations, cultivating manufacturing-specific data analytics talent through university-industry collaborations and targeted in-house training—prioritizing solutions to practical pain points like quality control and energy efficiency optimization over the blind pursuit of cutting-edge technologies. Additionally, firms should enhance technological collaboration with research institutions and industry leaders to develop implementable data analytics models, embedding data processing and analytics capabilities across the full R&D, production, and sales value chain to translate data value into tangible cost savings and operational efficiency gains.

4.2.3 Implementing Targeted Support Policies Based on Firm Heterogeneity

Governments must abandon a one-size-fits-all support approach and formulate targeted policies to facilitate firms' digital transformation. For firms with distinct ownership structures, the evaluation systems of state-owned enterprises (SOEs) should be optimized to incorporate core performance metrics such as cost control and efficiency improvements stemming from digital transformation. This guides SOEs to focus on digital upgrading of core businesses and industry chain collaborative transformation, allowing them to play a demonstrative leading role in the sector while curbing blind investment and resource waste. For non-state-owned enterprises, tiered special subsidies tied to digital investment intensity and cost-efficiency outcomes should be rolled out, complemented by tax incentives for equipment procurement and interest subsidies for digital transformation-specific loans—policies that directly address the financial and technological bottlenecks these firms face in their digital transition. For firms at different stages of the corporate life cycle, growing firms should be prioritized for support including technical diagnostics for digital transformation, guidance on scenario-specific solutions, and free basic talent training. This enables them to first complete lightweight digital upgrading of core processes such as production, delivering rapid cost-saving and efficiency-enhancing transformation outcomes. Mature firms should receive increased policy support for industrial internet platform development and in-depth digital technology application; they are encouraged to leverage their industrial leadership to drive collaborative digital transformation among upstream and downstream suppliers, further amplifying the positive spillover effects of digital transformation on corporate financial performance.

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Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

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