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COST OPTIMIZATION PATHWAYS DRIVEN BY DIGITAL FINANCE: EMPIRICAL EVIDENCE FROM DONGGUAN' S MANUFACTURING SECTOR

Jing Wang*, Ping Peng
School of Finance and Economics, Guangdong University of Science and Technology, Dongguan 523000, Guangdong, China.
Corresponding Author: Jing Wang, Email: 798999717@qq.com

Abstract: As an essential component of the digital economy, digital finance is gradually becoming a key driver of cost reduction, efficiency enhancement, and high-quality development for enterprises. This paper analyzes 4,054 panel data points from 588 listed manufacturing firms in Dongguan spanning 2015 to 2024. Using financial and innovation R&D data from the CSMAR database, and employing SPSS for multiple linear regression analysis, the study empirically investigates the mechanisms and pathways through which digital finance influences enterprise cost optimization. The results reveal: (1) digital finance and soft technology investments significantly increase total asset turnover, validating their role in enhancing resource allocation efficiency; (2) R&D investment exhibits dual effects—while the R&D expenditure ratio positively affects firm efficiency, excessive allocations to R&D personnel and direct inputs impose short-term cost burdens; (3) new productive forces exhibit a phased negative impact, suggesting that digital infrastructure has not yet been fully converted into cost advantages; (4) financial structure and profitability form the core support for cost optimization. The study provides empirical evidence for digital transformation in the manufacturing industry and offers policy recommendations for both enterprises and government bodies.
Keywords: Digital finance; Cost optimization; Manufacturing industry; Dongguan; Empirical analysis

1 INTRODUCTION

1.1 Research Background

Since 2015, China's digital economy has experienced sustained and rapid growth, with technologies such as fintech, artificial intelligence, and blockchain continuously reshaping the traditional financial service landscape. The widespread application of digital finance has not only revolutionized corporate financing models but also enhanced firms' operational efficiency and resource allocation capabilities through big data and information platforms.
At the same time, the manufacturing sector is facing rising raw material costs, energy price fluctuations, and increasing labor expenses, making traditional cost control methods less effective. As a key manufacturing hub in the Pearl River Delta, Dongguan has taken the lead nationally in industrial upgrading and digital transformation. However, many manufacturing firms still lag in terms of depth of digital finance adoption and the development of effective cost governance mechanisms. Whether digital finance can truly drive cost optimization in manufacturing enterprises has become a critical issue for both academic research and industrial practice.

1.2 Research Significance

Theoretically, this study extends the research boundary of digital finance and corporate cost governance by uncovering the micro-level mechanisms through which digital finance empowers resource allocation and cost control within enterprises. Practically, the findings offer empirical evidence to support digital transformation in manufacturing, not only in Dongguan but also nationwide. This contributes to promoting the integration of operations and finance as well as the implementation of intelligent and collaborative management systems.

2 LITERATURE REVIEW

2.1 International Research Progress

Foreign scholars have conducted extensive studies on the relationship between digital finance and firm performance, focusing mainly on financing constraints, innovation efficiency, and productivity improvement. Allen et al. found that digital finance reduces financing barriers and enhances liquidity for small and medium-sized enterprises by applying advanced information technologies[1]. Beck emphasized that digital finance serves not only as a financial innovation but also as a strategic mechanism for industrial transformation, which enhances operational efficiency by lowering transaction costs, increasing information transparency, and improving capital allocation[2]. The OECD highlighted an indirect facilitation effect, showing that digital finance improves cost efficiency and productivity through innovation investment and supply chain coordination[3]. Similarly, Porter's Value Chain Theory posits that competitive advantage depends on dynamic management of cost and differentiation, and the integration of digital technologies allows firms to achieve refined cost control and information sharing across the value chain[4].

In summary, international research views digital finance as a bridge connecting financial efficiency, innovation efficiency, and production efficiency, with mechanisms manifested in reduced financing costs, optimized innovation-resource allocation, and intelligent management decisions.

2.2 Domestic Research Progress

In China, the study of digital finance has expanded rapidly, emphasizing its role in innovation, cost governance, and industrial upgrading. Zhou Lian argued that digital finance promotes inclusive finance and structural transformation, serving as a key channel for strengthening the link between finance and the real economy[5]. Chen Wenling noted that by breaking information barriers, digital finance improves firms' access to financial data and enhances capital utilization efficiency[6]. Liu Yingchun proposed that digitalized management is a vital approach to cost optimization, as it enables real-time and visualized operational control[7]. Li Xiaoyan confirmed the mediating effect of digital finance on operational efficiency—it facilitates innovation input and alleviates financial constraints, indirectly improving profitability. Recent studies have also integrated digital finance with regional development[8]. Sun Jianbo found a significant positive correlation between digital finance development and manufacturing productivity at the regional level, indicating that regions with more advanced digital financial ecosystems tend to achieve higher resource allocation efficiency[9].

Overall, domestic literature has explored the importance of digital finance across policy, industry, and enterprise levels, yet there remains a lack of micro-level empirical evidence on cost governance. Most studies emphasize innovation or financing effects, with limited investigation into the mechanism through which digital finance influences cost efficiency via innovation inputs and financial structures.

2.3 Summary and Research Innovation

The existing literature provides a strong theoretical foundation for studying digital finance's impact on firm efficiency; however, three main gaps remain: (1) Macro bias – Research tends to focus on macroeconomic or sectoral effects, lacking enterprise-level empirical verification. (2) Incomplete mechanism analysis – The pathways linking digital finance to cost efficiency remain underexplored, particularly regarding innovation and financial structure as mediating channels. (3) Regional limitations – Few studies examine key manufacturing clusters such as Dongguan, limiting understanding of regional heterogeneity.

3 RESEARCH DESIGN

3.1 Data Sources and Sample Selection

This study focuses on manufacturing enterprises listed in Dongguan, Guangdong Province, during the period 2015–2024. All data were obtained from the China Stock Market & Accounting Research (CSMAR) database, including financial indicators, R&D input metrics, and firm characteristics. Financial firms and observations with excessive missing values were excluded. Continuous variables were winsorized at the 1st and 99th percentiles to mitigate the influence of outliers. The final balanced panel comprises 588 listed manufacturing firms with 4,054 firm-year observations, providing strong representativeness of the Pearl River Delta's digital transformation and cost governance dynamics.

3.2 Variable Design

3.2.1Dependent variable

Cost Efficiency (ATO)

Measured by Total Asset Turnover (ATO), which reflects how efficiently firms utilize assets to generate revenue:

$$\text{ATO}=\frac{\text{Operating Revenue}}{\text{Total Assets}} \tag{1}$$

A higher ATO indicates better asset utilization and stronger cost-control capability.

3.2.2 Core independent variables

To empirically examine the impact of digital finance and innovation activities on firms' technological upgrading, we construct a set of independent variables capturing different dimensions of innovation input and new productive forces. Specifically, we consider soft technology investment, R&D intensity, the proportion of R&D staff, the ratio of direct R&D investment, and the overall level of new productive forces. The definitions, symbols, and measurement methods of these independent variables are summarized in Table 1.

Table 1 Definitions and Measurements of Independent Variables (IV)

Variable Name	Symbol	Definition & Measurement
Soft Technology Investment (DF)	DF	Ratio of digital and IT expenditures to total operating cost, capturing the level of digital finance adoption.
R&D Intensity (RDE)	RDE	R&D expenditure as a proportion of operating revenue, measuring innovation investment strength.
R&D Staff Proportion (RDSTAFF)	RDSTAFF	Share of R&D employees in total staff, indicating the structure of human-capital investment in innovation.
Direct R&D Investment Ratio (RDDIRECT)	RDDIRECT	Direct R&D capital expenditure divided by total expenditures, representing innovation capital structure.
New Productive Forces Level (NP)	NP	Composite index based on automation, intelligent equipment, and digital system coverage, measuring technological upgrading.

3.2.3 Control variables

In addition to the above independent variables, this study also incorporates several firm-level characteristics as control variables to isolate the net effect of digital finance and innovation inputs on technological upgrading. Specifically, we control for financial leverage, liquidity, inventory management efficiency, and profitability, which may simultaneously influence firms' investment decisions and performance outcomes. The definitions and measurements of these control variables are presented in Table 2.

Table 2 Definition and Measurement of Control Variables (CV)

Variable Name	Symbol	Definition
Leverage Ratio (LEV)	LEV	Total liabilities divided by total assets, reflecting financial leverage.
Cash Ratio (CASH)	CASH	Cash and cash equivalents divided by current liabilities, indicating liquidity.
Inventory Turnover (INV)	INV	Operating cost divided by average inventory, reflecting efficiency of inventory management.
Return on Assets (ROA)	ROA	Net profit divided by total assets, capturing profitability.

3.3 Model Construction

This study employs a multiple linear regression model to assess the impact of digital finance and innovation variables on cost efficiency, specified as:

$$\mathbf{ATOi}=\beta_0+\beta_1\mathbf{DF}_i+\beta_2\mathbf{RDE}_i+\beta_3\mathbf{RDSTAFF}_i+\beta_4\mathbf{RDDIRECT}_i+\beta_5\mathbf{NP}_i+\beta_6\mathbf{LEV}_i+\beta_7\mathbf{CASH}_i+\beta_8\mathbf{INV}_i+\beta_9\mathbf{ROA}_i+\varepsilon_i$$

Where ATO_i denotes firm i's cost-efficiency indicator;DF_i represents digital-finance input; RDE_i， $RDSTAFF_i$ and $RDDIRECT_i$ correspond to innovation inputs;NP_i measures the level of new productive forces;LEV_i, $CASH_i$, INV_i and ROA_i serve as control variables;and ε_i is the error term.

All estimations were performed in SPSS 27.0, with variance inflation factor (VIF) tests conducted for multicollinearity and F/t-tests applied for overall and individual significance.

4 EMPIRICAL RESULTS AND ANALYSIS

4.1 Model Fit Evaluation

Based on 4,054 firm-year observations from 588 listed manufacturing enterprises in Dongguan over the period 2015–2024, multiple linear regression analysis was conducted using SPSS 27.0 to assess the impact of digital finance, R&D investment, and new productive forces on cost efficiency (measured by total asset turnover).

Table 3 Model Summary[b]

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	0.610[a]	0.372	0.371	.284657229	0.372	266.196	9	4044	0.000

Note: a: Predictors: (Constant), Return on Assets (ROA), Soft Technology Investment (DF), Inventory Turnover (INV), Direct R& D Investment Ratio (RDDIRECT), Cash Ratio (CASH), R&D Staff Proportion (RDSTAFF), R& D Intensity (RDE), Leverage Ratio (LEV), New Productive Forces Level (NP).
b: Dependent Variable: Total Asset Turnover (ATO).

As shown in Table 3, the model exhibits a correlation coefficient (R) of 0.610, indicating a strong linear relationship between the independent and dependent variables. The coefficient of determination (R^2) is 0.372, meaning that the nine independent variables jointly explain 37.2% of the variance in the dependent variable. The adjusted R^2 is 0.371, suggesting the model has strong explanatory power and stability. The F-statistic is 266.196 with a significance level of 0.000 ($p < 0.001$), thus rejecting the null hypothesis that all regression coefficients are zero.
This result demonstrates that digital finance, R&D activities, and financial structure variables significantly contribute to explaining enterprise asset utilization efficiency. In other words, cost efficiency in manufacturing is not driven by a single factor but arises from the coordinated influence of digital investment, innovation activities, and financial structure.

4.2 Analysis of Variance (ANOVA)

From the results in Table 4, the regression sum of squares accounts for 37.2% of the total sum of squares, aligning with the R^2 value and indicating a high degree of explanatory power. The F-test passed the 1% significance threshold ($p = 0.000$), confirming that the overall model is statistically significant.
The statistical significance of the model suggests that digital finance and innovation investments have a systematic and stable impact on asset turnover. Differences in efficiency across firms are structural rather than random, determined by differences in input structure and innovation levels.

Table 4 ANOVA[a]

	Model	Sum of Squares	df	Mean Square	F	Sig.
1	Regression	194.128	9	21.570	266.196	0.000[b]
	Residual	327.684	4044	0.081		
	Total	521.813	4053			

Note: a: Dependent Variable: Total Asset Turnover (ATO).
b: Predictors: (Constant), Return on Assets (ROA), Soft Technology Investment (DF), Inventory Turnover (INV), Direct R&D Investment Ratio (RDDIRECT), Cash Ratio (CASH), R&D Staff Proportion (RDSTAFF), R&D Intensity (RDE), Leverage Ratio (LEV), New Productive Forces Level (NP)

4.3 Regression Coefficients and Variable Significance

As shown in Table 5, all variables are statistically significant at the 1% level.
Soft Technology Investment (Digital Finance): Exhibits the largest standardized coefficient ($\beta = 0.421$), indicating the strongest positive impact on cost efficiency. The implementation of digital financial systems significantly improves fund allocation and asset turnover.
R&D Intensity: Has a significantly positive effect on total asset turnover, confirming that investment in innovation improves resource utilization and long-term competitiveness.
R&D Staff Proportion and Direct R&D Investment: Both exhibit negative coefficients, suggesting that the short-term costs of innovation—such as personnel and capital expenditure—can temporarily reduce cost efficiency. This highlights the "short-term cost effect" of R&D investment.
New Productive Forces: Also shows a negative coefficient, indicating that the initial phase of technological transformation and automation increases fixed investment. However, these costs are expected to be offset by efficiency gains in the long run.
Financial Structure Variables: Leverage ratio, inventory turnover, and return on assets are all positively associated with total asset turnover, implying that sound financial leverage and profitability are key to improving cost efficiency.
In summary, the model reveals a dual-track mechanism of "digital empowerment + innovation-driven" cost control: digital finance enhances transparency and capital efficiency, while R&D investment and technological transformation generate long-term spillover effects, collectively improving the enterprise's cost competitiveness.

Table 5 Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	0.382	0.017		22.255	0.000		
	R&D Intensity (RDE)	0.001	0.000	0.053	4.106	0.000	0.941	1.062
	Soft Technology Investment (DF)	71.027	2.774	0.421	25.603	0.000	0.573	1.744
	R&D Staff Proportion (RDSTAFF)	-0.002	0.000	-0.074	-5.597	0.000	0.886	1.129
	Direct R& D Investment Ratio (RDDIRECT)	0.103	0.009	0.217	11.346	0.000	0.426	2.346

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
New Productive Forces Level (NP)	-14.601	0.835	-0.381	-17.489	0.000	0.328	3.050
Leverage Ratio (LEV)	0.519	0.032	0.251	16.291	0.000	0.652	1.533
Cash Ratio (CASH)	-0.020	0.003	-0.092	-6.222	0.000	0.718	1.393
Inventory Turnover (INV)	0.003	0.001	0.083	6.633	0.000	0.980	1.021
Return on Assets (ROA)	1.777	0.066	0.375	27.001	0.000	0.807	1.239

Note: a: Dependent Variable: Total Asset Turnover (ATO).

4.4 Multicollinearity Diagnosis

Table 6 Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions									
				(Constant)	R&D Intensity (RDE)	Soft Technology Investment (DF)	R&D Staff Proportion (RDSTAFF)	Direct R&D Investment Ratio (RDDIRECT)	New Productive Forces Level (NP)	Leverage Ratio (LEV)	Cash Ratio (CASH)	Inventory Turnover (INV)	Return on Assets (ROA)
1	1	4.448	1.000	0.00	0.00	0.01	0.01	0.00	0.01	0.00	0.01	0.01	0.01
	2	1.271	1.870	0.00	0.06	0.00	0.00	0.10	0.04	0.00	0.05	0.03	0.09
	3	1.046	2.062	0.00	0.69	0.00	0.00	0.03	0.01	0.00	0.00	0.02	0.02
	4	0.856	2.279	0.00	0.04	0.10	0.00	0.08	0.00	0.01	0.26	0.01	0.01
	5	0.734	2.462	0.00	0.00	0.00	0.03	0.02	0.00	0.00	0.07	0.81	0.01
	6	0.615	2.689	0.00	0.09	0.16	0.13	0.00	0.02	0.02	0.00	0.00	0.22
	7	0.558	2.824	0.00	0.08	0.10	0.00	0.03	0.02	0.02	0.21	0.05	0.34
	8	0.304	3.824	0.01	0.02	0.02	0.59	0.02	0.02	0.09	0.08	0.06	0.11
	9	0.125	5.961	0.01	0.00	0.60	0.15	0.71	0.87	0.01	0.00	0.00	0.00
	10	0.044	10.044	0.96	0.01	0.00	0.07	0.00	0.02	0.84	0.31	0.01	0.18

Note: a: Dependent Variable: Total Asset Turnover (ATO).

As shown in Table 6, all variance inflation factor (VIF) values are below 4 and all tolerance values exceed 0.3, indicating that multicollinearity is not a concern. The independent variables maintain sufficient orthogonality.This confirms that digital finance, R&D input, and financial structure contribute independently to cost efficiency improvements, with limited redundancy among explanatory variables.

4.5 Residual Analysis and Robustness Testing

From Table 7, the mean of residuals is close to zero and the standard deviation of standardized residuals is approximately 1, satisfying the assumption of normality. The prediction errors are random and free from systemic bias.

Table 7 Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	-0.70622998	2.76746249	0.67534876	0.218854919	4054
Residual	-1.187158465	2.267492533	0.000000000	0.284341001	4054
Std. Predicted Value	-6.313	9.559	0.000	1.000	4054
Std. Residual	-4.170	7.966	0.000	0.999	4054

Note: a: Dependent Variable: Total Asset Turnover (ATO).

Figure 1 Shows a symmetric bell-shaped distribution with a mean near zero (3.10E-15) and a standard deviation of 0.999, indicating the residuals follow a normal distribution. Efficiency differences across firms primarily reflect actual operational differences rather than model misspecification.

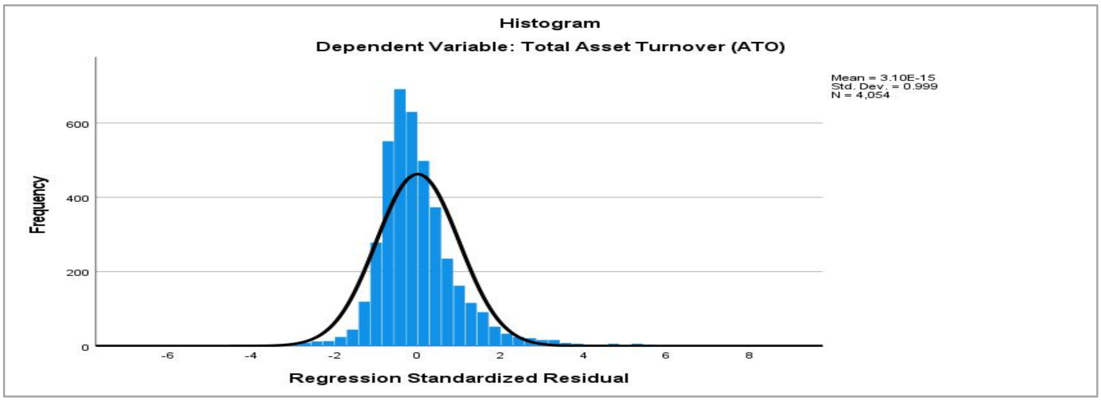

Figure 1 Histogram of Standardized Residuals

Figure 2 Observations are closely aligned with the 45-degree diagonal line, confirming good fit with the theoretical normal distribution. The model satisfies the normality assumption, enhancing the reliability and generalizability of statistical inference.

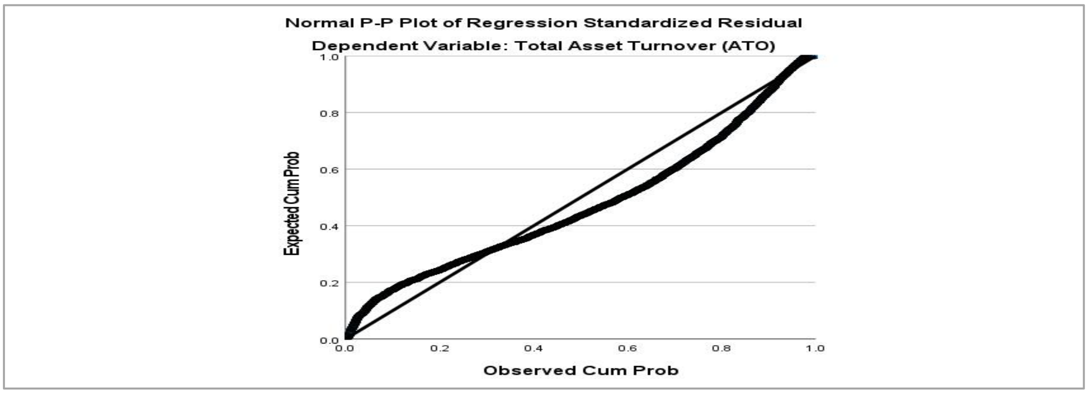

Figure 2 P-P Plot of Residuals

Figure 3 Points are randomly scattered around the horizontal axis without funnel-shaped or curved patterns, indicating no heteroskedasticity or autocorrelation. The model structure is robust, confirming that the effects of digital finance, innovation input, and financial structure on firm efficiency are linear and reliable.

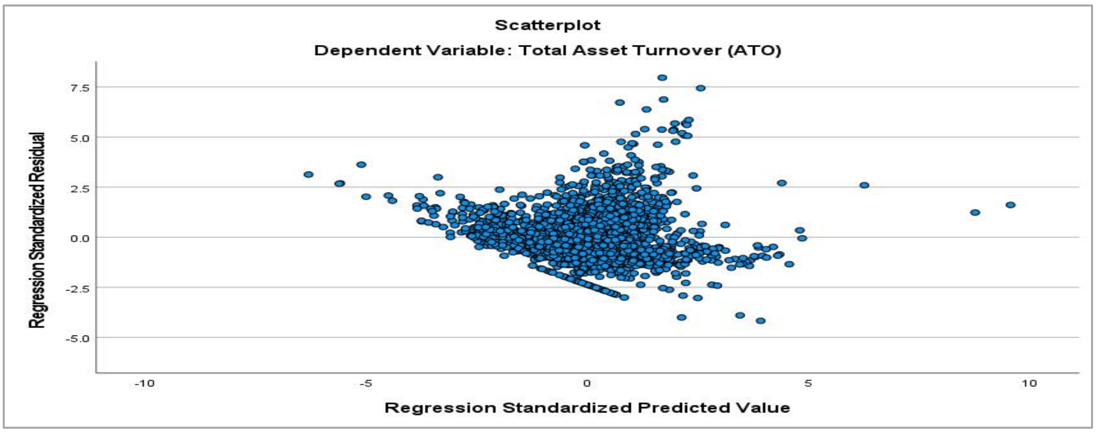

Figure 3 Scatter Plot of Standardized Residuals

5 CONCLUSIONS AND POLICY RECOMMENDATIONS

5.1 Research Conclusions

Based on an empirical analysis of 4,054 observations from 588 listed manufacturing enterprises in Dongguan between 2015 and 2024, this study constructed a cost efficiency influence model centered on four core components: digital finance, R&D investment, new productive forces, and financial structure. Regression results obtained via SPSS support the following main conclusions:

5.1.1 Digital finance significantly improves cost efficiency and serves as a core driver of cost reduction and efficiency enhancement

The regression results show that the digital finance variable (soft technology) has the highest standardized coefficient among all predictors (β = 0.421, $p < 0.001$), indicating its dominant role in promoting cost efficiency. Digital finance facilitates optimal capital allocation by improving financing accessibility, reducing transaction costs, and enhancing fund liquidity. This, in turn, boosts asset turnover and business performance in manufacturing enterprises.

5.1.2 Structural differences in R&D investment lead to phased effects on cost efficiency

R&D expenditure ratio exhibits a significant positive impact on cost efficiency (β = 0.053), suggesting that innovation funding enhances long-term competitiveness and resource efficiency. However, both the proportion of R&D staff (β = -0.074) and direct R&D investment ratio (β = -0.217) show significant negative effects, indicating that high upfront personnel and capital costs during early-stage innovation may temporarily increase operational costs. This dual nature of innovation activities—boosting output while potentially suppressing short-term efficiency—represents the "double-edged sword" effect of R&D.

5.1.3 New productive forces hinder short-term but promote long-term cost optimization

The coefficient for the new productive forces variable is negative (β = -0.381), reflecting that in the early stages of digital and smart transformation, firms face significant costs related to technological upgrades and equipment investments. However, such “pain-period” investments lay the foundation for future cost savings and efficiency gains, consistent with the classic “investment-before-return” diffusion curve of emerging technologies.

5.1.4 Financial structure and profitability provide stable support for cost governance

Both the leverage ratio (β = 0.251) and return on assets (β = 0.375) are significantly positive, indicating that moderate financial leverage and solid profitability help enhance capital utilization and cost management. Conversely, a high cash ratio (β = -0.092) negatively impacts investment efficiency, suggesting that overly conservative liquidity management may hinder optimal capital deployment.

5.1.5 Inventory management is a crucial internal factor for improving cost efficiency

Inventory turnover shows a positive association with cost efficiency (β = 0.083), confirming that manufacturing enterprises can reduce capital occupancy and warehousing costs through optimized inventory structures and supply chain coordination—thus improving overall operational performance.

In summary: The coordinated development of digital finance, innovation investment, and financial structure forms the strategic path for enterprises to achieve cost optimization and operational efficiency.

5.2 Policy Recommendations

5.2.1 Enhance digital financial infrastructure to extend services to manufacturing enterprises

Governments should accelerate the construction of digital financial infrastructure and promote open access to financial data. Collaboration among banks, technology firms, and industry platforms should be encouraged to develop fintech tools such as smart credit, blockchain settlement, and cloud-based payment systems. These tools can provide manufacturing firms—especially SMEs—with efficient, secure, and low-cost financing. Policy support should also be expanded to ensure inclusive access to fintech in manufacturing and to build a multi-level industrial financial ecosystem.

5.2.2 Establish incentive and risk-sharing mechanisms for R&D investment

Given the delayed returns and uncertainties of R&D, enterprises face high upfront risks in innovation. It is recommended that governments improve the R&D tax deduction policy and increase fiscal incentives for innovation expenditures. Special funds and grants should be established to support technological innovation and the commercialization of R&D results. Moreover, the government should foster collaborative innovation networks involving government, industry, academia, and research institutions, and direct financial and research resources toward high-potential innovation clusters.

5.2.3 Promote digital and intelligent transformation of manufacturing to create an “intelligence-driven efficiency” model

To address the short-term cost pressure from building new productive forces, a gradual digitalization strategy should be encouraged. Government subsidies for smart manufacturing equipment, support for digital factory pilots, and funding for “Industrial Internet+” initiatives can help firms manage early-stage investment burdens. By promoting cloud manufacturing and data collaboration platforms, upstream and downstream firms can share information and integrate resources across the value chain, enhancing overall cost control capacity.

5.2.4 Optimize enterprise financial structures to improve capital allocation efficiency

Governments and financial institutions should guide enterprises toward rational debt levels and establish capital efficiency-oriented financing evaluation mechanisms. New financing instruments such as green bonds and technology bonds should be promoted to diversify funding channels. Enterprises should also be encouraged to enhance accounting informatization and build financial risk warning systems. This will support the implementation of integrated finance-operations (F&O) systems and improve the efficiency of fund utilization.

6 CONCLUSIONS

Overall, digital finance, innovation-driven development, and financial structure optimization jointly shape the cost-efficiency landscape of manufacturing enterprises. Their interplay forms a dynamic system of “digital empowerment – innovation-driven – financial coordination.” In the digital economy era, only by leveraging the

catalytic power of digital finance, strengthening innovation capacity, and establishing robust financial management systems can enterprises shift from “cost advantages” to “efficiency advantages” within global value chains.
The experience of Dongguan’s manufacturing sector shows that digital finance is more than a technological innovation; it is a key driver of industrial upgrading and regional economic resilience. Looking forward, as big data and artificial intelligence become more deeply integrated, enterprise cost governance will evolve toward intelligent, networked, and collaborative systems—injecting long-term momentum into the high-quality development of China’s manufacturing industry.

COMPETING INTERESTS

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