Digital Transformation, Talent Development, and Corporate Financial Performance: Multi-Path Evidence from Chinese Manufacturing Firms

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ABSTRACT:
Digital transformation has become an important driver of organizational development, talent allocation, innovation capacity, and corporate performance. Drawing on dynamic capability theory and innovation theory, this study examines how digital transformation influences corporate financial performance through talent input and innovation output. Using data from Chinese listed manufacturing firms from 2014 to 2023, a multi-path mediation model was constructed and empirically tested. The findings show that digital transformation significantly improves financial performance. However, this effect does not follow the traditional linear pathway of "human resources → innovation → performance." Although digital transformation promotes the conversion of corporate inputs into innovation outputs, these outputs do not significantly translate into financial performance, indicating a mechanism break. The mediating and chain-mediating effects are not fully supported, suggesting that digital transformation operates through multiple parallel pathways rather than a single progressive mechanism. Heterogeneity analysis further shows that the effect is more significant among state-owned firms. This study provides implications for digital skills development, workforce adaptation, organizational learning, and sustainable enterprise development.

Keywords: Manufacturing Enterprises, Digital Transformation, Corporate Financial Performance, Workforce Adaptation.

1. Introduction

Against the backdrop of rapid development in the digital economy, Digital transformation (DT) has become a crucial path to improve corporate financial performance (FP). However, a noteworthy issue exists: despite continuous investment in DT, FP has not improved proportionally, and the relationship between the two is even unstable. This phenomenon of "increased investment → performance uncertainty" prompts deeper reflection: why can't DT consistently translate into improved FP?

Existing research generally explores the impact of DT on FP from the perspective of resource

optimization and efficiency improvement. Some scholars believe that DT can improve information processing efficiency, optimize processes, and reduce costs, thereby enhancing FP (Liu et al., 2023). It can also optimize resource allocation through technological innovation, thereby improving operational performance (Ali et al., 2024). Meanwhile, some studies, considering the Chinese context, have found that DT helps improve productivity and innovation capabilities (Xing et al., 2023). However, another type of research points out that the economic effects of DT are uncertain. On the one hand, digital investment is usually accompanied by high upfront costs, and its benefits have a significant lag(Hossnofsky & Junge, 2019); on the other hand, firms may face path dependence and insufficient capabilities during the DT process, resulting in low "input → output" conversion efficiency(Xiong & Li, 2026). Therefore, some empirical studies have found that the impact of DT on FP is not significant, and may even show a negative or unstable relationship in the short term (Yonghong et al., 2023). In summary, the academic community has not yet reached a consensus on the relationship between DT and corporate FP. The key question is whether DT can be effectively transformed into economic value.

Based on dynamic capability theory (DCT), on the one hand, Al Jabri et al. (2024) pointed out that firms' dynamic capabilities are strengthened through DT. Digital technologies not only enhance organizations' ability to perceive and respond to the external environment, but also promote the restructuring of corporate capabilities through IT alignment and resource integration, thereby driving the improvement of organizational agility and innovation capabilities. On the other hand, even if an firm possesses technological and informational advantages, it may still fail to achieve performance improvement due to insufficient resource allocation capabilities or low innovation transformation efficiency (Yonghong et al., 2023). In the context of DT, some scholars view digital technology as an important tool for enhancing corporate perception capabilities, while resource allocation and innovation activities correspond to capturing and transforming capabilities (Al Jabri et al., 2024; Warner & Wäger, 2019), respectively. However, existing research mostly remains at the theoretical level, lacking systematic empirical testing on how these three types of capabilities work synergistically and whether there is a structural imbalance.

Existing research on the mechanisms of DT primarily focuses on its mediating effects. Some literature argues that DT indirectly impacts corporate FP through pathways such as promoting technological innovation, optimizing resource allocation, and improving governance structures (Liu et al., 2024). For example, R&D investment is widely considered a key mediating variable in the impact of DT on FP. Furthermore, some studies have attempted to construct multi-mediation or chain-mediation models, suggesting that corporate FP depends on the continuous effects of multiple mechanistic variables (Ali et al., 2024; Liu et al., 2024). However, these studies typically implicitly assume a stable transmission relationship between the mediating variables. It is noteworthy that a growing body of research is questioning this linear transmission assumption. Zhao et al. (2025) pointed out that the effectiveness of digital capabilities depends on the synergistic effect of resource allocation capabilities. If firms lack an effective resource allocation mechanism, digital investment will be difficult to fully transform into innovation performance, which will lead to a certain degree of uncertainty in the effect of the transmission path.

While existing research has explored the impact of DT on corporate FP from multiple perspectives, it still has the following shortcomings: First, most studies assume that DT directly improves corporate FP, neglecting its non-linear effects. Second, the mechanisms by which DT operates are mostly focused on single paths, lacking a multi-dimensional capability perspective. Third, explanations for why DT may not fully translate into performance are

insufficient. Therefore, this study attempts to investigate the following questions:

1. Can dynamic capability building promote the realization of the financial benefits of corporate digital transformation?
2. Is the structure of its mechanism stable, or are there structural breaks?
3. Is the effect of digital transformation context-dependent?

To verify the above questions, this study constructs an analytical framework that integrates direct effects and multi-path mechanisms. From three dimensions: digital words frequency, capital investment intensity, and R&D investment intensity, it systematically examines the impact mechanism of DT on corporate FP. In terms of mechanism identification, this study not only examines the independent action paths of different resource elements but also tests the potential chain transmission mechanism of "talent costs→innovation output" to identify the structural characteristics and transmission boundaries of the DT mechanism.

The study found that: First, DT has a significant direct impact on corporate FP overall, but digital word frequency (perception) has a lagged negative effect; Second, capital expenditure and R&D investment have a significant positive impact on corporate FP, with R&D investment playing a more prominent role; Third, the mechanism by which DT affects corporate FP exhibits a disconnect; Fourth, the performance-promoting effect of capital expenditure is mainly concentrated in state-owned firms, while digital word frequency shows a more significant negative effect in state-owned firms.

The contributions of this study are threefold: First, it breaks through the traditional linear mediation framework, revealing the phenomenon of "mechanism fracture" in DT; second, it explains the phenomenon of "capability enhancement but incomplete value realization" in DT from the perspectives of dynamic capability theory and innovation theory; third, it reveals the heterogeneous characteristics of the effects of DT from the perspective of institutional and firm heterogeneity.

The structure of this study is as follows: Part II constructs the theoretical analysis and proposes research hypotheses; Part III introduces the data sources and research design; Part IV reports and analyzes the empirical results; Part V presents the discussion; and finally, the conclusions and policy implications are presented.

2. Theoretical Basis and Research Hypotheses

2.1 Theoretical Basis

To explain the varying economic effects of DT, an increasing number of studies have introduced dynamic capability theory (DCT). This theory posits that firms in a dynamic environment utilize three types of capabilities(perception, capture, and transformation) to identify and utilize external opportunities (Warner & Wäger, 2019). Specifically, perception capability emphasizes a firm's ability to identify market changes and technological trends; capture capability is reflected in resource allocation and investment decision-making; and transformation capability is manifested in the ability to convert resources into innovative achievements and economic benefits. Existing research indicates that different capability dimensions play differentiated roles in the formation of firm performance (Li et al., 2018).

Innovation theory (IT) emphasizes that firms promote innovation output through technological investment and knowledge accumulation, and achieve performance improvement through innovation activities (Xie et al., 2018). However, the transformation of innovation results into economic performance does not occur automatically, but is constrained by multiple factors such as organizational structure, resource allocation efficiency, and market environment (Zou, 2024). Therefore, even if DT can improve innovation output, its impact on FP may still be insignificant or unstable (Li et al., 2023). This manifests as "innovation exists, but its transformation is insufficient."

2.2 Research Hypotheses

I. Digital Perception Capability and Corporate Financial Performance

Within the framework of DCT, firms first need the ability to identify changes and opportunities in the external environment, i.e., "perception capability." DT through the application of big data technology, enhances information acquisition and environmental identification capabilities, thereby strengthening opportunity perception(Li et al., 2018; Warner & Wäger, 2019). However, perception capability itself does not directly create economic value; its role is mainly reflected in "discovering opportunities" rather than "realizing value"(Warner & Wäger, 2019) .Therefore, without resource allocation and innovation transformation capabilities, digital perception capability is unlikely to improve FP (Zhao et al., 2025). Furthermore, DT is usually accompanied by high investment, and its positive effects often have a certain lag (Du & Wang, 2024). Based on this, the following hypothesis is proposed:

H1: Digital perception capabilities have no direct impact on corporate financial performance, but their effects are delayed.

II. Resource Acquisition Capability and Corporate Financial Performance

After identifying opportunities, firms need to transform potential opportunities into concrete actions (capture capability) through resource allocation. Capital investment, as a key manifestation of corporate resource allocation, reflects a company's ability to internalize external opportunities into internal resources (Lovallo et al., 2020). Theoretically, DT helps firms improve resource allocation efficiency and investment decision-making capabilities. On the one hand, digital technology can alleviate information asymmetry and improve the accuracy of firms' judgments on market demand and investment directions (Feng et al., 2024); on the other hand, digital tools can optimize the efficiency of internal resource coordination, thereby increasing the return on capital investment (Liu & He, 2024). Therefore, reasonable capital investment can promote improved production efficiency and operational performance (Lovallo et al., 2020). However, compared to perception capabilities, resource capture capabilities have entered the stage of internal resource operation within the firms. It is closer to the value creation process and has a more significant positive impact on corporate FP. Therefore, the following hypothesis is proposed:

H2: In digital transformation, resource capture capabilities have a significant positive impact on corporate financial performance.

III. Resource Conversion Capability and Corporate Financial Performance

After completing resource allocation, firms need to further transform resources into actual output through R&D innovation and technological upgrades. R&D investment, as a crucial manifestation of corporate innovation activities, is an important indicator for measuring resource conversion capability (Taherdoost, 2024). Compared to perception capability and resource capture capability, resource conversion capability has a more direct impact on corporate value creation. It can drive corporate FP growth through technological innovation and efficiency improvement (Zhang et al., 2021). Therefore, Wang et al. (2022) emphasized that R&D investment is generally considered an important driver of improving corporate FP. Based on this, the following hypothesis is proposed:

H3: Resource conversion capability has a significant positive impact on corporate financial performance.

IV. Digital Transformation, Talent Costs, and Corporate Financial Performance

DT relies not only on technological investment but also on the support of high-quality digital talent. Talent costs reflect a firm's investment level in human capital, skills training, and the acquisition of professional talent (Suseno & Pinnington, 2018). Afshari and Hadian Nasab (2021) pointed that by increasing investment in talent costs, firms can enhance their organizational learning and innovation

capabilities. And it can improve resource integration efficiency and digital application capabilities, ultimately promoting improved corporate FP. However, talent investment also has characteristics such as long cycles, high costs, and uncertain short-term returns, and its performance effects may vary at different stages (Urban, 2018). Specifically, in the early stages of DT, talent investment is more of a cost expenditure; its positive value will gradually be released as the organization learns and accumulates capabilities (Zhang & Chen, 2024). Based on this, to propose the following hypothesis:

H4: Talent costs may play a mediating role between digital transformation and corporate financial performance.

V. Digital Transformation, Innovation Output, and Corporate Financial Performance

Innovation output reflects a firm's ability to transform R&D resources into technological achievements and market value, and is a key indicator of corporate innovation performance (Medda, 2020). The application of digital technologies can reduce information costs and improve R&D efficiency, thereby enhancing the level of corporate innovation output. Simultaneously, innovation output can further drive product upgrades and market expansion, bringing sustainable competitive advantages to firms (Zhang et al., 2021). However, (Wang et al., 2022) pointed that innovation activities may exhibit a phenomenon of "high input, low conversion," meaning that R&D investment fails to effectively generate innovative results. Therefore, the impact of DT on FP still depends on whether innovative results can be successfully commercialized (Li et al., 2023). Based on this, the following hypothesis is proposed:

H5: Innovation output may play a mediating role between digital transformation and corporate financial performance.

VI. The chain mechanism between talent costs and innovation output

Dynamic capability theory (DCT) emphasizes that DT can only truly translate into performance advantages when firms can effectively identify opportunities, allocate resources, and achieve innovation transformation (Al Jabri et al., 2024; Li et al., 2018; Warner & Wäger, 2019). However, in reality, stable connections between different capability dimensions are not necessarily formed. On the one hand, although firms possess strong information perception capabilities, they may be unable to complete resource allocation in a timely manner due to organizational inertia, resource constraints, or governance deficiencies (Lovallo et al., 2020; Zhao et al., 2025); on the other hand, even if firms invest resources, they may struggle to generate actual innovative results due to insufficient innovation efficiency or failed technology transformation (Wang et al., 2022; Zou, 2024). This leads to a phenomenon of "capability disruption" in the dynamic capability chain. This capability disruption means that the impact of DT on FP may not be achieved through a complete chain path, but rather exhibits phased, discontinuous, or even partially ineffective characteristics. That is, the traditional chain mediation mechanism may not be stably valid. Therefore, the following hypothesis is proposed:

H6: The impact of digital transformation on corporate financial performance may not have a significant complete chain mediation effect.

3. Methodology

3.1 Model Design

To examine the direct impact of DT on corporate FP, this study constructs the following two-way fixed effects model:

$$Y_{i,t} = \alpha_0 + \alpha_1 X1_{i,t} + \alpha_2 X2_{i,t} + \alpha_3 X3_{i,t} + \alpha Controls_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (X \rightarrow Y)$$

Where: $Y_{i,t}$ represents the corporate FP (e.g., gross profit margin); $X1_{i,t}$, $X2_{i,t}$, and $X3_{i,t}$ represent the level of DT (e.g., digital words frequency, capital expenditure intensity, and R&D investment intensity); $Controls_{i,t}$ represents a set of control variables, including debt-to-equity ratio, current asset turnover, total

assets, and revenue growth rate; a_0 is a constant term; α_1, α_2, and α_3 represent the impact coefficients of DT on the corporate FP; α is the coefficient vector of the control variables; μ_i represents firm fixed effects; λ_t represents time fixed effects; and $\varepsilon_{i,t}$ represents the random disturbance term.

To further investigate the mechanism by which DT affects corporate FP, this study constructs a chain mediation mechanism of "talent costs (M1) → innovation output (M2)".

This study constructs a chain mediation mechanism of "talent costs → innovation intensity" using a stepwise regression method.

Mediating effect of talent costs (M1):

$$Y_{i,t} = \beta_0 + \beta_1 X1_{i,t} + \beta_2 X2_{i,t} + \beta_3 X3_{i,t} + \beta_4 M1_{i,t} + \beta Controls_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (X \rightarrow M1 \rightarrow Y)$$

Mediating effect of innovation output (M2):

$$Y_{i,t} = \theta_0 + \theta_1 X1_{i,t} + \theta_2 X2_{i,t} + \theta_3 X3_{i,t} + \theta_4 M2_{i,t} + \theta controls_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (X \rightarrow M2 \rightarrow Y)$$

M1→M2 chain mediation mechanism:

$$M2_{i,t} = \delta_0 + \delta_1 X1_{i,t} + \delta_2 X2_{i,t} + \delta_3 X3_{i,t} + \delta_4 M1_{i,t} + \delta controls_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (X \rightarrow M1 \rightarrow M2)$$

Complete chain model:

$$Y_{i,t} = \gamma_0 + \gamma_1 X1_{i,t} + \gamma_2 X2_{i,t} + \gamma_3 X3_{i,t} + \gamma_4 M1_{i,t} + \gamma_5 M5_{i,t} + \gamma controls_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (X \rightarrow M1 \rightarrow M2 \rightarrow Y)$$

3.2 Data Sample

The data for this study comes from the CSMAR database, with a sample period from 2014 to 2023. Select sample firms that are normally listed on the main board A-shares, and successively remove firms with missing equity structure and financial industry firms. Subsequently, a sample of manufacturing firms was selected, and samples with missing key variables (such as talent costs and R&D investment) were further removed to construct a balanced panel data set, ultimately yielding a sample of 604 valid firms. For the 17 firms marked as ST or *ST during or at the end of the sample period, they were retained due to their relatively complete long-term data (approximately 10 years) to ensure sample continuity and data integrity. To reduce the impact of extreme values on the estimation results, this study performs tailing on continuous variables at the 1% level and logarithmic transformation on relevant variables to alleviate heteroscedasticity and improve data distribution. All data processing and empirical analysis were performed using Stata 18.0.

3.3 Variable definition

This study selects DT as the core explanatory variable and constructs proxy variables from three dimensions: digital perception (digital words frequency), resource integration (capital expenditure intensity), and transformation capability (R&D investment intensity) to measure the level of corporate DT. This setting is based on the multidimensional attributes of DT, including both information disclosure at the strategic awareness level and resource investment and technology transformation processes. This is basically in line with the research framework of dynamic digital capability decomposition (Leso et al., 2024). Meanwhile, this study selects gross profit margin as a core indicator of corporate financial performance (FP). This indicator can effectively reflect the profitability of a firm's main business and has strong robustness and comparability (Lee, 2023). Therefore, this combination of variables can comprehensively reflect the impact mechanism of DT on corporate value creation.

To control for the impact of firm heterogeneity on the research results, this study introduces a set of control variables. Specifically, the debt-to-equity ratio reflects the level of financial risk of the firm, the current asset turnover ratio measures the firm's operational efficiency, the revenue growth rate controls for differences in firm growth, and total assets reflect the firm's asset size. See Table 1 for details.

Table 1: Main variable definitions

Type	Variable Name	Symbol	Definition
Explained variable	Gross Profit Margin	Y	Revenue Minus Cost of goods sold) / Revenue
Core Explanatory Variable	Digital Words Frequency	X1	Number of times digital-related words (AI, big data, cloud computing, blockchain, etc.) appear in the annual report
	Capital expenditure intensity	X2	Capital expenditure / Operating revenue
	R&D intensity	X3	R&D investment / operating revenue
Mediating variable	Talent Costs	M1	Employee compensation, training expenses, and consulting fees within Administrative Expenses
	Innovation Output	M2	Intangible assets / Operating revenue
Control variables	Asset-liability Ratio	Lev	Total Liabilities / Total Assets
	Current Asset Turnover Ratio	CAT	Revenue / Average Current Assets.
	Revenue Growth Rate	Growth	(Current Period Revenue - Previous Period Revenue) / Previous Period Revenue
	Total Assets	TA	Total Assets listed in the report
dependent variable replacement	Operating Profit Margin	OPM	Operating profit / Operating revenue

4. Results

4.1 Descriptive Statistical Analysis

Table 2 shows the descriptive statistics for each variable. The standard deviations for digital words frequency (X1), capital expenditure intensity (X2), and R&D intensity (X3) are 1.207, 0.096, and 0.030, respectively, with means of 1.380, 0.086, and 0.043, indicating differences among manufacturing firms in their strategic emphasis on DT, capital expenditure, and R&D intensity. The standard deviation for talent costs (M1) is 1.138, with a mean of 8.983, indicating differences in talent costs (TC) among different manufacturing firms. The standard deviation for innovation output (M2) is 0.095, with a mean of 0.090, indicating differences in innovation output (IO) among different manufacturing firms. The mean for gross profit margin (Y) is 0.267, with a standard deviation of 0.154, indicating differences in gross profit margin among different manufacturing firms.

Table 2: Descriptive Statistics

	N	Mean	SD	Min	Max
X1	6040	1.380	1.207	0.000	4.605
X2	6040	0.086	0.096	0.003	0.557
X3	6040	0.043	0.030	0.001	0.169
Lever	6040	0.412	0.168	0.085	0.779
CAT	6040	1.325	0.829	0.283	5.226
TA	6040	22.499	1.088	20.359	25.632
growth	6040	0.123	0.279	-0.455	1.593
M1	6040	8.983	1.138	5.357	11.746
M2	6040	0.090	0.095	0.004	0.614
Y	6040	0.267	0.154	0.027	0.766

Note: Gross Profit Margin(Y), Digital words Frequency (X1), Capital Expenditure Intensity (X2), Talent Costs (M1), Innovation Output (M2), Debt-to-Equity Ratio (Lever), Current Asset Turnover (CAT), Total Assets (TA), Revenue Growth Rate (growth)

4.2 Correlation Analysis

Table 3.1 reports the correlation coefficient matrix of the main variables. Overall, the correlations between the variables are largely consistent with economic theory expectations. Specifically, digital words frequency (X1) shows a weak positive correlation with firm performance (Y). This indicates that the impact of digital words frequency on firm performance is relatively limited. In contrast, capital expenditure intensity (X2) and R&D investment intensity (X3) are both significantly positively correlated with corporate FP, preliminarily indicating that resource input and technological innovation are important factors affecting corporate FP. In addition, there is a certain correlation between digital words frequency and mediating variables (M1, M2), which provides preliminary support for subsequent mechanism testing. Regarding control variables, the debt-to-equity ratio is significantly negatively correlated with corporate FP (coefficient: -0.380, $p < 0.01$), while the revenue growth rate is significantly positively correlated with FP (coefficient: 0.0699, $p < 0.01$), both in line with economic expectations.

Furthermore, the absolute values of the correlation coefficients among the variables are generally low, and the VIF values are all below 3, not exceeding the commonly used threshold (VIF=5). This indicates that the model does not have a serious multicollinearity problem. (See Appendix A)

Table 3: Correlation Analysis

	X1	X2	X3	Lever	CAT	TA	growth	M1	M2	Y
X1	1									
X2	-0.111***	1								
X3	0.200***	0.199***	1							
Lever	0.0518***	-0.0186	-0.144***	1						
CAT	-0.0782***	-0.165***	-0.370***	0.191***	1					
TA	0.150***	0.0263**	-0.0845***	0.439***	0.214***	1				
growth	0.0275**	0.0179	-0.0593***	0.0182	0.138***	0.0746***	1			
M1	0.164***	-0.0995***	-0.0702***	0.360***	0.248***	0.790***	0.0333***	1		
M2	-0.117***	0.350***	0.222***	-0.0673***	-0.260***	-0.0840***	-0.0579***	-0.147***	1	
Y	0.0323**	0.121***	0.285***	-0.380***	-0.326***	-0.100***	0.0699***	-0.0382***	0.176***	1

t statistics in parentheses

** p < 0.1, ** p < 0.05, *** p < 0.01*

4.3 Benchmark Regression Analysis

Table 4 reports the baseline regression results of DT on corporate FP. Columns (1) and (2) are the OLS estimation results, and columns (3) and (4) are the estimation results of the two-way fixed effects model. Robust correction was applied to all results.

From the overall model perspective, the explanatory power of the model is significantly improved after introducing control variables. Further, by adopting the two-way fixed effects model, the R^2 values of the OLS model significantly increased from 0.086 and 0.260 to 0.885 and 0.896. This indicates that unobservable heterogeneity at the firm level has a significant impact on corporate FP. This also reveals that the fixed effects model can more effectively control for individual differences, thereby improving the reliability of the estimation results.

Regarding the core explanatory variables, digital words frequency (X1) failed the significance test in all models, indicating that the level of external communication regarding DT does not have a significant direct impact on corporate FP. This result reveals that the economic effects of corporate DT may have a certain lag or be realized through indirect mechanisms. In contrast, capital expenditure intensity (X2) and R&D investment intensity (X3) both showed significant positive effects in different models, indicating that corporate resource investment and technological innovation are important drivers of improved corporate FP. Thus, hypotheses H1, H2, and H3 were validated.

Regarding control variables, the debt-to-equity ratio has a significant negative impact on corporate FP, indicating that a high level of financial leverage may inhibit corporate profitability. The Current Asset Turnover (CAT) result also shows a negative impact, indicating a phased inhibitory effect of DT in manufacturing firms. For example, in the initial stage, resource reallocation and increased investment lead to a temporary decrease in the efficiency of current asset utilization. Both corporate asset size and revenue growth rate show significant positive effects, consistent with existing research conclusions.

Based on the above analysis, this study, through benchmark regression analysis, concludes that DT has a significant positive impact on corporate FP, with both capital investment and R&D investment showing stable positive effects.

Table 4: Results of Benchmark Regression Analysis

	(1)	**(2)**	**(3)**	**(4)**
	OLS（robust）	**OLS（robust）**	**FE（robust）**	**FE（robust）**
	No control variables added	**Add control variables**	**No control variables added**	**Add control variables**
X1	-0.0020	-0.0019	-0.0009	-0.0015
	(-1.205)	(-1.282)	(-0.749)	(-1.247)
X2	0.1043***	0.0612***	0.0380***	0.0312**
	(4.908)	(3.130)	(2.851)	(2.334)
X3	1.4136***	0.8113***	0.3141***	0.2785***
	(18.190)	(10.051)	(2.899)	(2.721)
Lever		-0.3343***		-0.1562***
		(-26.246)		(-12.534)
CAT		-0.0433***		-0.0162***
		(-22.735)		(-4.432)
TA		0.0165***		0.0149***
		(8.624)		(3.903)
growth		0.0602***		0.0383***
		(8.228)		(8.860)
_cons	0.2001***	0.0469	0.2515***	-0.0002
	(50.825)	(1.199)	(51.661)	(-0.002)
N	6040	6040	6040	6040
R^2	0.086	0.260	0.885	0.896

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.4 Robustness Testing and Endogeneity Treatment

To enhance the reliability of the baseline regression results, this study further examined the results from three aspects: sample processing, variable substitution, and endogeneity treatment. All results were obtained using a two-way fixed effect (robust). The specific details are shown in Table 5.

As shown in column (1), the baseline regression results show that the digital words frequency (X1) has no significant effect on the dependent variable (-0.0015). However, after excluding special years, as shown in column (2), its result shows a weakly significant negative effect (-0.0024, $p<0.1$), indicating that its short-term effect may be affected by external shocks. At the same time, this result further supports the possibility that there may be certain cost adjustments and efficiency losses in the early stages of DT.

Capital expenditure intensity (X2) was significantly positive in the baseline model (0.0312, $p<0.05$), but the estimation results fluctuate under different robustness test settings. After excluding special years, the effect of this variable is no longer significant, indicating that its effect was context-dependent and unstable. R&D investment intensity (X3) was significantly positive in both the baseline and robust models (0.2785, 0.3219, both $p<0.01$). However, when the explained variable was replaced by operating profit margin (OPM), the result, as shown in column (3), turned negative (-1.3351, $p<0.01$). This indicates that its impact on different performance indicators has structural differences. This also shows that R&D investment has a more direct impact on costs and gross profit margins during DT than on short-term profit realization.

To further test the robustness of the sample, this study excluded ST and *ST firms (17 firms). The results of the re-regression, as shown in column (4), show that the coefficients of the core explanatory variables remain consistent and the conclusions have not changed substantially, indicating that the research results are not affected by abnormal firm samples and have strong robustness.

Regarding control variables, the debt-to-equity ratio (Lever) was significantly negative in all models (e.g., -0.1562, $p<0.01$), indicating that financial leverage inhibits corporate FP. The current asset turnover ratio (CAT) was significantly negative (-0.0162, $p<0.01$), supporting the existence of efficiency loss effects in the early stages of DT. Firm size (TA) and growth showed significantly positive overall (e.g., growth was 0.0383, $p<0.01$), indicating that size and growth opportunities help improve FP. Overall, the model fit was high (R^2 approximately 0.896), and the results showed strong robustness.

While instrumental variables are a common approach to address endogeneity, in the context of this study, macro-level instrumental variables (such as regional digital infrastructure or policy shocks) are insufficient to effectively reflect the heterogeneity of DT at the firm level and may directly impact corporate FP, making it difficult to satisfy the exclusivity constraint. Therefore, referencing relevant research (Arkhangelsky et al., 2024; Wooldridge, 2025), this study employs a two-way fixed effects model combined with lagged terms of explanatory variables to mitigate potential endogeneity issues.

The results, as shown in Table (5), indicate that the digital words frequency (X1) was significantly negative after a one-period lag (-0.0034, $p<0.01$). This suggests that the emphasis on DT has a lagged and short-term inhibitory effect on corporate FP. Meanwhile, the positive impact of R&D investment intensity (X3) is persistent, but its marginal effect weakens (0.1708, $p<0.1$). In contrast, capital expenditure intensity (X2) is no longer significant in the lagged model (-0.0077), suggesting that its impact may be more of a short-term effect or unstable. Overall, the core variables are generally consistent in direction under the lag setting, supporting the robustness of the benchmark regression results and mitigating the endogeneity problem caused by reverse causality to some extent.

In summary, the robustness test results support the main conclusions of the benchmark regression and indicate that the impact of DT on corporate FP has a lagged characteristic.

Table 5: Robustness Test and Endogeneity Treatment Results

	(1) Baseline regression FE (robust)	(2) Excluding special years 2020-2021	(3) Operating profit margin (Replace Y)	(4) Excluding ST/*ST	(5) Lag Explanation Variables (L.)
X1	-0.0015	-0.0024*	0.0000	-0.0021*	-0.0034***
	(-1.247)	(-1.759)	(0.022)	(-1.765)	(-2.668)
X2	0.0312**	0.0244	0.1023***	0.0370***	-0.0077
	(2.334)	(1.631)	(3.777)	(2.800)	(-0.531)
X3	0.2785***	0.3219***	-1.3351***	0.3033***	0.1708*
	(2.721)	(2.614)	(-8.100)	(2.925)	(1.757)
Lever	-0.1562***	-0.1489***	-0.4243***	-0.1617***	-0.0783***
	(-12.534)	(-10.871)	(-20.005)	(-13.026)	(-6.172)
CAT	-0.0162***	-0.0171***	0.0033	-0.0148***	-0.0158***
	(-4.432)	(-4.039)	(0.914)	(-3.965)	(-4.391)
TA	0.0149***	0.0135***	0.0544***	0.0166***	-0.0018
	(3.903)	(3.094)	(9.769)	(4.286)	(-0.452)
growth	0.0383***	0.0341***	0.0828***	0.0371***	0.0195***
	(8.860)	(7.052)	(12.382)	(8.490)	(4.949)
_cons	-0.0002	0.0319	-0.9455***	-0.0393	0.3551***
	(-0.002)	(0.329)	(-7.555)	(-0.453)	(4.108)
N	6040	4832	6040	5870	5436
R^2	0.896	0.898	0.603	0.897	0.899

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.5 Mediation Effect Test

To further explore the mechanism by which DT affects corporate FP, this study constructed a mediation effect model to test both independent and chain mediation effects. A two-way robust fixed effects model was used for both tests, and the results are shown in Table 6.

Columns (1) ,(2), and (3) report the regression results of the mediation model X–M1–Y. The results show that both capital expenditure intensity (X2) and R&D investment intensity (X3) have a significant positive impact on FP. However, in the X→M1 path, the impact of the relevant variables on talent costs (M1) did not reach statistical significance, indicating that no significant promoting effect of DT on corporate talent investment has been found. Meanwhile, digital words frequency (X1) did not show significance in any model, indicating its relatively limited impact. Furthermore, the mediating variable talent costs (M1) showed a significant positive impact on FP (coefficient of 0.0038), indicating its important role in improving corporate FP. In summary, since the X→M1 path is not significant, talent costs failed to play a significant mediating role between DT and FP, and this mediating effect is not supported by experience.

Columns (1), (3), and (4) show the results of the mediation model X-M2-Y. Both capital

expenditure intensity (X2) and R&D investment intensity (X3) have a significant positive impact on FP, and both also significantly promote innovation output (M2). However, the impact of innovation output (M2) on FP did not reach statistical significance, indicating that it failed to mediate the relationship between DT and FP. This result may suggest that there is a time lag in the conversion of corporate innovation output into financial performance (FP), or that it is constrained by conversion efficiency.

The results in columns (6) and (7) show that, in the model including multiple mediating variables, capital expenditure intensity (X2) and R&D investment intensity (X3) both maintain significant positive effects on innovation output (M2) and FP(Y), indicating that they play a stable and important role in promoting corporate innovation and performance improvement.

However, in the chain mediation test, the paths X→M1, M1→M2, and M2→Y all failed the significance test, indicating that the impact of DT on corporate FP cannot be realized through the continuous transmission mechanism of "talent costs—innovation output," and its effect is more reflected in direct effects or other unobserved mechanisms.

Furthermore, talent costs (M1) showed a significant positive impact on FP in the final model, indicating its independent contribution to improved corporate FP, but it did not mediate the relationship between DT and innovation output.

Overall, the study did not find a significant chain mediation effect, but certain local interactions existed among the variables, suggesting that the impact mechanism of DT on corporate FP is complex and has not yet formed a stable transmission chain. This result indicates that the effect of DT on corporate FP relies more on the direct driving effect of capital and R&D investment, while an effective synergistic mechanism has not yet been established between human capital and innovation output.

Table 6: Results of Mediation Effect Detection

	(1) Y X-Y	***(2) M1 X-M1***	***(3) Y X-M1-Y***	***(4) M2 X-M2***	***(5) Y X-M2-Y***	***(6) M2 X-M1-M2***	***(7) Y X-M1-M2-Y***
X1	-0.0015	0.0066	-0.0015	-0.0015	-0.0016	-0.0015	-0.0016
	(-1.247)	(0.720)	(-1.268)	(-1.295)	(-1.294)	(-1.283)	(-1.314)
X2	0.0312**	-0.0854	0.0315**	0.1156***	0.0357***	0.1154***	0.0359***
	(2.334)	(-0.935)	(2.359)	(6.472)	(2.677)	(6.466)	(2.697)
X3	0.2785***	0.7981	0.2754***	0.4745***	0.2968***	0.4760***	0.2935***
	(2.721)	(1.431)	(2.691)	(5.254)	(2.851)	(5.271)	(2.821)
M1			0.0038**			-0.0019	0.0038**
			(2.226)			(-1.206)	(2.185)
M2					-0.0385		-0.0379
					(-1.509)		(-1.485)
_cons	-0.0002	-5.7142***	0.0217	-0.0370	-0.0016	-0.0478	0.0199
	(-0.002)	(-9.409)	(0.250)	(-0.398)	(-0.019)	(-0.513)	(0.230)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	6040	6040	6040	6040	6040	6040	6040
R^2	0.8958	0.8668	0.8959	0.7487	0.8959	0.7488	0.8960

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.6 Heterogeneity Analysis

To further examine the structural differences in the impact of DT on corporate FP, this study divided the sample into state-owned enterprises (SOEs) and non-state-owned enterprises (non-SOEs) based on ownership structure for grouped regression analysis. The results, shown in Table 7, reveal significant heterogeneity in the impact of DT on corporate FP across different ownership structures, with SOEs exhibiting a significantly stronger DT effect than non-SOEs.

Specifically, in the SOEs sample (1), the coefficients for capital expenditure intensity (X2) and R&D investment intensity (X3) were 0.0547 and 0.3465, respectively, and were significant. This indicates that SOEs, with institutional support and resource allocation advantages, are more likely to transform digital investment into performance improvement. In contrast, in the non-SOEs sample, the significance of capital expenditure intensity(X2) was significantly weakened, while R&D investment intensity (X3) still had a certain promoting effect on corporate FP. This shows that the role of R&D investment in DT is significant and not constrained by the nature of ownership. However, the impact of digital words frequency (X1) on FP exhibits heterogeneity in ownership. In SOEs, it may have a negative effect due to formal disclosure or resource misallocation, while in non-SOEs, its actual effect is not significant.

The above results indicate that the economic effects of DT are not homogeneous but exhibit significant differences under different ownership structures.

Table 7: Heterogeneity Detection (State-owned firms vs. non-state-owned firms)

	(1) SOEs	**(2)** non-SOEs
X1	-0.0042**	-0.0007
	(-2.116)	(-0.481)
X2	0.0547**	0.0208
	(2.192)	(1.298)
X3	0.3465***	0.2634**
	(2.707)	(1.966)
_cons	0.0741	-0.0301
	(0.628)	(-0.272)
Control variables	Yes	Yes
N	2004	4036
R^2	0.903	0.894
adj. R^2	0.890	0.881

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5. Discussion

Based on dynamic capability theory (DCT) and innovation theory (IT), this study systematically examines the mechanism by which DT affects corporate FP. The results show that DT has a significant positive impact on corporate FP, but its mechanism is not the linear transmission path of "input → innovation → performance" assumed by traditional theories. Instead, it exhibits a multi-path structure rather than a single linear transmission mechanism.

From the perspective of DCT, DT is essentially a process of firms perceiving their environment, restructuring resources, and reallocating capabilities. This study shows that DT can significantly promote the conversion of capital expenditure and R&D investment into innovative output, indicating that firms possess a certain "capability restructuring effect" in the digital

environment. However, this capability has not been further and stably converted into corporate FP, indicating a break in dynamic capabilities at the value realization stage (Liu & He, 2024; Zhao et al., 2025). Furthermore, this study found that capital expenditure and R&D investment can significantly improve innovative output, but innovative output has not significantly translated into performance, indicating a disconnect between resource "ownership" and "value realization." This result suggests that relying solely on resource input is insufficient to form a sustainable competitive advantage; resource conversion efficiency has become a key bottleneck (Lovallo et al., 2020).

From the perspective of IT, DT can significantly promote innovation output, indicating that technology and digital capabilities do indeed contribute to the generation of corporate innovation activities (Li et al., 2018; Li et al., 2023). However, the impact of innovation output on FP has not been significant, meaning that the transformation of innovation results into economic performance is not automatic but may be constrained by factors such as organizational structure, market environment, and the efficiency of results transformation. In other words, an increase in a firm's "increased innovation capabilities" does not necessarily translate into "improved FP." This finding expands the applicability of innovation theory in the digital context.

Further continuous mediation tests revealed the validity of the "talent cost-innovation output" chain mediation mechanism, indicating that human capital investment has not yet formed a stable transmission channel between DT and innovation. This result suggests that while human capital investment has a direct positive impact on corporate FP to some extent, its synergistic effect with innovation output is not yet fully realized and may be constrained by organizational synergy efficiency or resource allocation mechanisms (Afshari & Hadian Nasab, 2021).

Heterogeneity analysis further revealed that DT has a significantly stronger impact on SOEs than on non-SOEs (Song et al., 2026). This difference may stem from differences in institutional environment and resource access capabilities: SOEs have advantages in policy support and resource allocation, making it easier for them to translate digital investment into performance, while non-SOEs may be affected by market constraints and resource limitations.

In summary, the impact of DT on corporate FP exhibits a clear multi-path parallel characteristic. On the one hand, it forms a direct effect through capital expenditure and R&D investment; on the other hand, the transmission effect through the innovation output path is relatively limited, and the chain mediation mechanism is not supported. Therefore, the results of this study indicate that the mechanism of DT is closer to the structural characteristics of "direct effect dominance + partial innovation path existence + chain mechanism failure," rather than a traditional single linear transmission model. This finding, from the perspective of combining DCT and IT, provides new empirical evidence and boundary condition identification for the mechanism of DT.

6. Conclusion

6.1 Conclusions

This study, based on a sample of listed manufacturing firms in China, systematically examines the impact of DT on corporate FP from a multi-path mechanism perspective. The study finds that DT has a significant positive impact on corporate FP, but this is mainly achieved through direct effects. Capital expenditure and R&D investment play key roles in this process.

The mechanism test results indicate that DT can effectively promote the transformation of input factors into innovative outputs, but innovative outputs have not been stably converted into corporate FP, indicating a significant "innovation transformation break." Furthermore, the chain-mediated mechanism between talent costs and innovative outputs is not supported, further suggesting that the formation mechanism of corporate FP is more likely to be a multi-path

parallel structure rather than a single chain structure.

Overall, the mechanism by which DT affects corporate performance exhibits a structural characteristic of "direct effects dominating, multiple paths coexisting, and chain transmission not holding true." This finding not only enriches the theoretical explanatory framework of DT but also provides new empirical evidence for understanding its true mechanism of action in improving corporate FP.

6.2 Theoretical Contributions

First, this study expands the theoretical framework for explaining the impact of DT on corporate FP from a multi-path perspective. The research reveals that the impact of DT on corporate FP manifests as a direct effect, while also exhibiting some unstable indirect paths. This finding differs from existing studies that emphasize a single linear mediating path of "DT→innovation→performance," enriching the theoretical understanding of the mechanism of DT.

Second, based on DCT, this study reveals the crucial role of resource input in DT. The results show that capital expenditure and R&D investment have a significant direct promoting effect on corporate FP. This indicates that improving FP through resource restructuring is an important mechanism for realizing the benefits of DT. This finding strengthens the applicability of DCT in the digital context.

Third, this study finds that although DT can promote innovation output, innovation output does not significantly translate into corporate FP. This suggests that the linear assumption of "innovation→ performance" may be limited in the digital context. This finding provides new empirical evidence and boundary conditions for innovation theory.

6.3 Practical Implications

Firm Implications: In advancing their digital strategies, firms should pay greater attention to the efficiency of allocating key resources such as capital expenditure and R&D investment, and improve performance by enhancing direct operational capabilities. Simultaneously, they should prioritize building mechanisms for the transformation of innovative achievements, improving the efficiency of converting innovation into economic performance, rather than merely focusing on the quantitative growth of innovative output. Furthermore, human capital investment needs to be matched with organizational collaboration mechanisms to avoid a disconnect between resource input and innovative output.

Policy Implications: Policymakers should avoid viewing DT simply as a tool for "automatically improving performance," and instead focus on its heterogeneous performance across different industries and firm types. When promoting digital strategies, governments should strengthen the construction of innovation achievement transformation systems, such as improving technology markets and enhancing industry-academia-research collaboration mechanisms, to improve the efficiency of transforming innovation into economic performance. Furthermore, emphasis should be placed on the efficiency of internal resource allocation and organizational capacity building within firms, promoting the deep integration of digital capabilities with the real economy through institutional supply, thereby enhancing the actual economic benefits of DT.

6.4 Limitations

This study still has certain limitations. First, the research data mainly comes from listed firms, which may lead to sample selection bias and make it difficult to fully reflect the situation of SMEs. Second, although the study uses a fixed-effects model and lagged variables to mitigate endogeneity issues, it still cannot completely eliminate potential reverse causal relationships. Finally, the mechanism variables are mainly constructed based on observable indicators, which may not fully capture the complex capability evolution process within firms.

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