Research on the Mechanism of Digital Transformation Driving Supply Chain Performance Improvement Based on the Mediating Effect of Information Flow, Financial Flow, and Physical Flow

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Abstract. Existing research has insufficiently explored the mechanisms through which digital transformation affects supply chain performance. This study, using small and medium-sized manufacturing enterprises as a sample and based on 365 questionnaires, employs PLS-SEM to empirically examine the relationship between the two as well as the mediating effects of financial flow, information flow, and physical flow. The results indicate that digital transformation significantly and positively enhances supply chain performance, with the mediating effects of financial flow, information flow, and physical flow decreasing in that order. The study clarifies the underlying logic, providing a basis for corporate and government decision-making.

Keywords: Digital Transformation, Supply Chain Performance, Small and Medium-Sized Manufacturing Enterprises

1 Introduction

Supply chain performance is a core indicator measuring enterprises' resource allocation efficiency, responsiveness, and customer value realization. Its optimization can help enterprises cope with market fluctuations, reduce costs, and enhance competitiveness, while inefficient supply chains may trigger problems such as supply disruptions and high costs, threatening enterprise survival[1]. After the COVID-19 pandemic, global supply chain uncertainty has intensified, enterprises' demand for supply chain stability and resilience has significantly increased, driving academia to explore paths for improving its performance through technological upgrading and management model innovation.

Existing studies mostly analyze the influencing factors of supply chain performance from dimensions such as industry social capital, enterprise collaborative integration , and internal management effectiveness, but few studies have explored the internal logic of digital transformation affecting supply chain performance through specific intermediate mechanisms. As a process innovation relying on technologies such as big data and

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cloud computing, the connection and mechanism of supply chain digitalization with supply chain performance have not been clarified, and there is still no consensus on whether it can improve enterprises' risk resistance capabilities [2].

To address the research gap, this study is based on data from 365 small and medium-sized manufacturing enterprises and uses PLS-SEM to explore the impact mechanism of digital transformation on supply chain performance, as well as the mediating role of the financial flow , information flow, and physical flow. The study clarifies the causal relationships and transmission paths, offering both theoretical contributions and practical reference value.

2 Hypothesis Construction

2.1 Digital Transformation and Supply Chain Performance

Empowered by technologies such as big data and the Internet of Things, digital transformation breaks down supply chain information barriers, enables real-time sharing of various data, enhances enterprises' information integration and collaboration capabilities, promotes the supply chain's specialized operations and optimal resource allocation, and ultimately reduces operating costs, shortens response cycles, and improves performance levels. Existing studies have confirmed that supply chain digitalization can help enterprises quickly respond to customer needs, enhance agility [3], and play a key role in establishing trust and transparency and optimizing product quality [4]. Based on this, the following hypothesis is proposed:

H1: Digital transformation level (DT) has a significant positive impact on supply chain performance (SCP).

2.2 Mediating Roles of Information Flow, Financial Flow, and Physical Flow

Information flow breaks down information barriers among nodes, realizes real-time data sharing and precise integration, and lays the foundation for upstream and downstream collaboration; financial flow optimizes capital allocation through digital payment tools, shortens turnover cycles, reduces financing costs; physical flow relies on intelligent warehousing and dynamic distribution networks to improve material scheduling efficiency and reduce delivery cycles and inventory levels. Based on this, the following hypotheses are proposed:

H2: Information flow (Info) plays a significant mediating role between digital transformation (DT) and supply chain performance (SCP);

H3: Financial flow (Fin) plays a significant mediating role between digital transformation (DT) and supply chain performance (SCP);

H4: Physical flow (Phys) plays a significant mediating role between digital transformation (DT) and supply chain performance (SCP).

2.3 Theoretical Framework

The theoretical framework constructed in this study focuses on the direct impact of core dimensions of digital transformation on supply chain performance, and introduces information flow, financial flow, and physical flow as mediating variables to analyze the heterogeneity of their transmission paths. To control confounding factors, referring to existing research paradigms, enterprise establishment years, number of employees, business categories, annual turnover, and enterprise nature are taken as control variables to exclude their independent impact on supply chain performance. The research framework is shown in Figure 1.

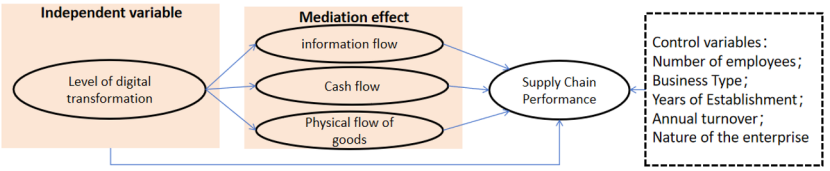

Fig. 1. Research Framework of the Impact of Enterprise Digital Transformation Degree on Supply Chain Performance. Source: Author's original

3 Data and Research Methods

3.1 Sample and Data Collection

This survey was conducted among small and medium-sized manufacturing enterprises nationwide in October 2025. Questionnaire links were distributed via WeChat. After optimizing the questionnaire logic and expression through a pre-survey of 30 people, formal distribution was carried out using the Wenjuanxing platform. To ensure data quality, screening mechanisms such as unique questionnaire links, unique IP addresses, and a response time of 5-10 minutes were set up, and invalid questionnaires with 5 consecutive identical answers were excluded, resulting in 365 valid samples.

Sample characteristics are shown in Table 1: All enterprises are in the manufacturing industry, private enterprises account for 79.180%, the core group is small and medium-sized enterprises with fewer than 500 employees and annual turnover of less than 50 million yuan, and the establishment years are concentrated in 4-10 years (accounting for 49.600%).

Table 1. Distribution of Basic Characteristics of Surveyed Sample Enterprises.

Sample Characteristics	Specific Classification	Frequency	Percentage (%)
Number of Enterprise Employees	1-50 people	112	30.680
	51-100 people	184	50.410
	101-500 people	69	18.900
	501-1000 people	0	0.000
	More than 1000 people	0	0.000

Sample Characteristics	Specific Classification	Frequency	Percentage (%)
Business Type	Manufacturing	365	100.000
	Retail	0	0.000
	Logistics	0	0.000
	Services	0	0.000
	Others (e.g., agriculture, wholesale)	0	0.000
Enterprise Establishment Years	1 year and below	38	12.900
	2-3 years	66	24.400
	4-5 years	116	28.200
	6-10 years	89	21.400
	11-20 years	39	13.200
	More than 20 years	17	4.660
Annual Turnover	10 million yuan and below	141	38.630
	10.01-50 million yuan	141	38.630
	50.01-100 million yuan	57	15.620
	100 million-1 billion yuan	26	7.120
	More than 1 billion yuan	0	0.000
Enterprise Nature	Private enterprise	289	79.180
	State-owned enterprise	32	8.770
	Foreign-funded enterprise	31	8.490
	Joint venture	13	3.560
Total	-	365	100.000

3.2 Measurement Methods

The questionnaire includes two parts: basic enterprise information and core construct measurement. Items for digital transformation level are adapted from Wu et al.[5] and Wang et al.[6]; items for information flow are from Wang et al. and Yuan[7]; items for financial flow and physical flow are adapted from Yin [8] and Yuan ; items for supply chain performance are adapted from Wu. All constructs are measured using a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree).

3.3 Analysis Methods

This study adopts the PLS-SEM method, which has the following advantages: it is suitable for complex models with mediating effects, imposes no strict normal distribution requirement on data, is applicable to both exploratory and confirmatory research with strong explanatory power, and can flexibly address the issue of factor uncertainty. The sample size of this study is 365; the analysis is conducted using SmartPLS 4.0, and significance testing is performed with 5,000 bootstrap resamplings.

4 Data Analysis and Results

4.1 Common Method Variance and Descriptive Statistics

Harman's single-factor test shows that the first factor explains 42.350% of the total variance, which is lower than the critical value of 50% , indicating that common method variance has no significant impact .

Descriptive statistics show that the mean values of the three mediating variables range from 3.390 to 3.464, and the standard deviations range from 1.152 to 1.174, indicating that the digitalization level of various supply chain processes is coordinated; the mean value of digital transformation level is significantly higher than that of supply chain performance (mean difference 0.350, $p<0.001$), indicating an "investment-performance gap" in transformation; the standard deviation of supply chain performance is 0.863, showing small differences in enterprise performance levels.

4.2 Measurement Model

Construct reliability was evaluated through Cronbach's alpha and Composite Reliability (CR). Table 2 shows that both Cronbach's alpha and Composite Reliability are higher than the critical value of 0.700, which means the scale has good internal consistency.

Table 2. Reliability and Validity Test of Constructs.

Construct	Vif	Items	Standard loadings	Cronbach'α	CR	AVE
DT	1.656	In the supply chain, our company has a high level of adoption of artificial intelligence (AI), blockchain, cloud computing, Internet of Things (IoT), and big data analytics technologies.	0.833	0.798	0.881	0.712
	1.797	The enterprise has formulated feasible digital supply chain digitalization strategies.	0.863			
	1.672	The enterprise aims to achieve information exchange through digitalization and strengthen the linkage between different business processes.	0.835			
Info	1.793	The enterprise can communicate with partners in real-time through the digital supply chain system.	0.847	0.801	0.883	0.715

Construct	Vif	Items	Standard loadings	Cronbach'α	CR	AVE
Fin	1.608	The enterprise can quickly share various data with partners through the digital supply chain system.	0.837	0.778	0.871	0.693
	1.799	The integrated system enables the enterprise to jointly predict and plan future demand with supply chain partners.	0.854			
	1.663	The company provides clear and accurate payment documents.	0.846			
	1.578	When the enterprise ships goods to supply chain partners, the accounts receivable process is automatically triggered.	0.827			
	1.592	When the enterprise receives goods from supply chain partners, the accounts payable process is automatically triggered.	0.824			
Phys	1.748	Our company ensures order fulfillment with the exact quantity required.	0.844	0.818	0.892	0.734
	1.958	The enterprise and supply chain partners work together to reduce inventory holdings.	0.877			
	1.797	The enterprise and supply chain partners jointly allocate product flow directions.	0.847			
SCP	1.576	Our company is satisfied with the overall speed of supply chain processes and has an excellent on-time delivery record.	0.799	0.735	0.835	0.560
	1.613	The length of supply chain processes is shortening.	0.810			
	1.385	Our company's supply chain can provide a high level of customer service.	0.697			
	1.219	Our supply chain can support us to quickly launch new products to the market.	0.678			

Note: (1) CR is the abbreviation of Composite Reliability; (2) AVE is the abbreviation of Average Variance Extracted. DT=Digital Transformation Level; Info=Information Flow; Fin=Financial Flow; Phys=Physical Flow; SCP=Supply Chain Performance. Source: Author's research

Convergent validity reflects whether measurement items reflect the same construct. This study uses Average Variance Extracted (AVE) and standardized factor loadings for evaluation. The results show that the factor loadings of all items are greater than 0.700, meeting the basic requirements. In addition, as shown in Table 3, the AVE values of all constructs are higher than 0.500, indicating good convergent validity.

Discriminant validity was measured through Heterotrait-Monotrait Ratio (HTMT) and Fornell-Larcker criterion. This criterion requires that the square root of the Average Variance Extracted (AVE) of each construct must be greater than its correlation coefficient with other constructs. Table 4 shows that the HTMT ratios of all construct combinations are lower than 0.850. Therefore, all constructs have good discriminant validity. Table 5 shows the results of Indirect Effects, Direct Effects, and Total Effects。

Table 3. Correlation Coefficients and Square Roots of AVE Among Constructs.

	DT	Fin	Info	Phys	SCP
DT	0.844				
Fin	0.509	0.832			
Info	0.505	0.517	0.846		
Phys	0.515	0.578	0.603	0.856	
SCP	0.566	0.580	0.490	0.485	0.748

Note: Diagonal elements are the square roots of the Average Variance Extracted (AVE) of each construct; off-diagonal elements are the correlation coefficients between constructs. DT=Digital Transformation Level; Info=Information Flow; Fin=Financial Flow; Phys=Physical Flow; SCP=Supply Chain Performance. Source: Author's research

Table 4. Heterotrait-Monotrait Ratio (HTMT).

	DT	Fin	Info	Phys	SCP
Fin	0.647				
Info	0.630	0.655			
Phys	0.636	0.726	0.746		
SCP	0.737	0.763	0.632	0.623	

Note: Table elements are the correlation coefficients between constructs. DT=Digital Transformation Level; Info=Information Flow; Fin=Financial Flow; Phys=Physical Flow; SCP=Supply Chain Performance. Source: Author's research

Table 5. Results of Indirect Effects, Direct Effects, and Total Effects.

	Specific indirect effects			Total indirect effects			Direct effects			Total effects		
Hypotheses and paths	β	T-value	Confidence intervals	β	T-value	Confidence intervals	β	T-value	Confidence intervals	β	T-value	Confidence intervals
DT→Phys→SCP	0.033	1.140	[0.021,0.092]									
DT→Info→SCP	0.067	2.282	[0.010,0.125]	0.263	8.325	[0.204,0.328]	0.304	6.515	[0.211,0.397]	0.567	16.989	[0.501,0.632]
DT→Fin→SCP	0.163	5.903	[0.111,0.220]									

4.3 Predictive Relevance

The coefficient of determination (R^2) shows that R^2=0.260 for financial flow (Fin) (weak predictive power) and R^2=0.454 for supply chain performance (SCP) (moderate to strong predictive power) . The Stone-Geisser criterion (Q^2) shows that Q^2=0.192 for physical flow (Phys) (moderate predictive effect) and Q^2=0.375 for information flow (Info) (strong predictive effect) , indicating good predictive relevance of the model[9].

5 Discussion

This study verifies the positive driving effect of digital transformation on the supply chain performance of small and medium-sized manufacturing enterprises and clarifies the mediating transmission mechanism of the financial flow , information flow, and physical flow. The main conclusions are as follows:

First, digital transformation significantly improves supply chain performance, which echoes other research on the impact of digital transformation on ESG performance. Through the integration of technologies such as the Internet of Things and big data, digital transformation promotes the evolution of the supply chain into a networked and adaptive system [10], integrates manufacturing units and information systems, optimizes supply-demand docking, and achieves cost reduction, efficiency improvement, and quality enhancement [11].

Second, the "three flows" all serve as mediators with heterogeneous effects. Financial flow has the strongest mediating effect, as it is directly bound to payment systems and financial platforms in digital transformation. Its optimization shortens capital turnover, reduces financing costs. Physical flow has the weakest mediating effect, as it relies on the transformation of hardware facilities and physical networks with long cycles and high costs.

6 Conclusions, Implications, and Limitations

6.1 Conclusions

Based on data from 365 small and medium-sized manufacturing enterprises, this study confirms that digital transformation has a significant positive impact on supply chain performance, and information flow, financial flow, and physical flow play mediating roles between them, among which financial flow has the strongest mediating effect, followed by information flow, and physical flow is the weakest. The study reveals the economic value of digital transformation in the post-pandemic era and provides theoretical and empirical support for enterprise transformation and performance improvement.

6.2 Implications

At the enterprise level, digital transformation should be regarded as a core strategy. Enterprises should deploy technologies such as artificial intelligence and blockchain, improve their digital strategy systems, enrich their reserve of digital talents, build intelligent capital settlement systems, and upgrade logistics, warehousing and distribution networks.

At the government level, special support funds should be established to subsidize enterprises in technology procurement, equipment upgrading and talent training. The government should build public digital service platforms, encourage the construction of demonstration projects, promote industry-university-research collaboration, cultivate compound digital talents, and strengthen technical research and development as well as application support.

6.3 Limitations

This study has the following shortcomings: first, cross-sectional data are used, which cannot dynamically track the long-term changes in the relationship between variables; second, the research objects are limited to small and medium-sized manufacturing enterprises, and the generalizability of the conclusions needs further verification; third, only enterprises in China are focused on, and no comparative analysis of foreign enterprise scenarios is involved. In the future, the research can be improved by expanding the research objects, and conducting cross-country comparisons.

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