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Digital Transformation's Impact on Supply Chain Efficiency: Evidence from China's Listed Manufacturing Firms

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Abstract

This study investigates the impact of digital transformation (DT) on supply chain efficiency (SCE) in Chinese listed manufacturing firms using panel data from 2014–2023. Employing two-way fixed-effects and instrumental variable models, results show that DT significantly improves SCE. Mediation analysis reveals that this effect operates through two key mechanisms: enhancing technology development rate (TDR) and improving operational management efficiency (OME). Robustness checks with alternative variables confirm the consistency of the findings. The study highlights the strategic value of integrating digital tools into innovation and management processes, offering empirical evidence for policy support and enterprise decision-making to foster end-to-end digital adoption in manufacturing supply chains.

Keywords: DT, Supply Chain Efficiency, Technology Development Rate, Operational Management

Introduction

In the era of rapid digital evolution, digital transformation (DT) has emerged as a crucial strategic imperative for enterprises seeking resilience, competitiveness, and sustainable development. Nowhere is this more evident than in the manufacturing sector, which serves as the cornerstone of the real economy and a key engine of industrial upgrading. As global supply chains become increasingly complex and vulnerable to disruption, enhancing supply chain efficiency (SCE) through digital tools is not merely a technological upgrade—it is a necessity for survival and growth (Negi, 2020; Wang et al., 2022).

In China, the world's largest manufacturing powerhouse, the government has recognized the transformative power of DT. Policy frameworks such as the *14th Five-Year Plan for Digital Economy Development, Made in China 2025*, and the *Industrial Internet Innovation and Development Action Plan* reflect a strong national commitment to accelerating DT across the industrial landscape. These initiatives aim to build flexible, intelligent, and coordinated supply chains that can adapt to volatility while supporting high-quality economic development.

While the adoption of digital technologies—such as big data, artificial intelligence, and cloud platforms—has expanded rapidly in Chinese manufacturing (Owusu-Berko, 2025), existing studies have primarily focused on the positive effects of DT on firm performance, innovation capability, and operational efficiency, mostly from the perspectives of organizational change, process reengineering, and innovation-driven development (Chukwudi, 2024; Ha et al., 2022; Hao et al., 2023). However, the practical effectiveness of DT in improving supply chain efficiency (SCE) remains underexplored, particularly in emerging economy contexts. In particular, current research has rarely unpacked the internal mechanisms through which DT enhances supply chain performance.

This study aims to fill that gap by empirically investigating whether and how DT improves SCE among Chinese listed manufacturing firms. It focuses on TDR and OME as key transmission channels, offering a comprehensive framework that connects digital investment with tangible supply chain outcomes. By clarifying these internal drivers, the study provides deeper insights into how digital initiatives translate into real efficiency gains.

By focusing on the mechanisms of technology development and operational management, the study not only reveals the pathways through which digitalization creates value but also provides empirical insights into the measurable benefits of DT. These insights are particularly valuable for business leaders seeking to optimize operations, policymakers aiming to design effective digital economy strategies, and scholars interested in the evolving interplay between technology and industrial performance.

Therefore, this research contributes to both theory and practice by advancing our understanding of DT's role in supply chain optimization. It also offers actionable evidence for firms striving to build digital capabilities and for governments developing supportive policy environments in the digital age.

Literature Review and Research Hypothesis

The Impact of DT on SCE in CMCs

CMCs is currently undergoing a critical shift from large-scale growth to high-quality development. With the deepening of the digital economy, DT has become a strategic pathway for firms to enhance competitiveness and achieve sustainable growth. DT is not limited to the adoption of new technologies; it also involves a comprehensive restructuring of organizational structures, business processes, and management models at the strategic level (Nour & Arbussà, 2024; Wang et al., 2023). As a pillar of the national economy, the manufacturing industry bears the responsibility of transformation and upgrading in the wave of intelligence and informatization. The development of digital capabilities has become a key driver for improving operational efficiency and market responsiveness.

In the context of rapidly evolving digital environments, SCE in manufacturing firms is undergoing structural reconstruction. SCE reflects not only the rational allocation of resources and coordination capacity within firms, but also their ability to respond quickly to market changes and deliver quality services (Zhao et al., 2023). Recent studies widely agree that DT significantly enhances the efficiency of information flow and resource utilization in the supply chain. On one hand, the integration of digital technologies enables manufacturing firms to achieve transparency, real-time visibility, and intelligent control throughout the supply chain,

thus improving responsiveness and coordination (Alonge et al., 2021; Patil, 2024). On the other hand, data-driven forecasting models and intelligent scheduling systems help optimize material management and inventory control, reducing waste and operating costs (Tripathi et al., 2022). Moreover, digital systems strengthen firms' ability to anticipate and respond to disruptions, such as logistics delays or supply interruptions, thereby improving overall supply chain resilience and adaptability.
Based on this, the following hypothesis is proposed:
H1: *DT improves the SCE of listed manufacturing firms in China.*

The Mechanisms Linking DT to SCE in CMCs
The improvement of SCE in CMCs relies heavily on two core capabilities. The first is continuous innovation on the technological front, which enables intelligent, modular, and flexible production (Liu et al., 2023). The second is process optimization in management, which enhances responsiveness in production planning, inventory control, and logistics coordination (Ayomide & Ozurumba, 2024). Accordingly, technology R&D and operational efficiency represent two critical pathways—technological support and process execution—through which DT affects supply chain performance. Based on this framework, the current study investigates the mediating effects of Technology Development Rate (TDR) and operational management efficiency (OME).

Innovation-Driven Pathway via TDR
Technology R&D is essential for manufacturing firms to improve product quality and process sophistication. DT injects new momentum into R&D activities (Liu & He, 2024). Manufacturing supply chains are complex, involving materials, components, production, logistics, and inventory. These processes demand close coordination across all links, and digital technologies enhance this coordination by improving demand-supply matching accuracy and reducing external transaction costs. These effects are more significant in manufacturing firms with high levels of competition (Yang et al., 2021).

In the context of listed CMCs, digital tools accelerate the collection, processing, and analysis of R&D data. They also support new R&D models such as remote collaboration and virtual simulation testing, improving the overall efficiency of R&D investment (Wang et al., 2022). More importantly, strong R&D capabilities enable localized production of core components and support the modularization and standardization of product design. These improvements help optimize material planning and streamline production, enhancing stability and control in upstream supply chain operations (Uche Nweje & Moyosore Taiwo, 2025). For example, Siemens applied in-house developed digital twin technology to achieve real-time coordination across the supply chain. This reduced downtime by 30%, increased output by 25%, and cut maintenance costs by 20%, significantly improving SCE.

In addition, enhanced R&D reduces reliance on external suppliers by enabling internal integration of resources. This strengthens the firm's position in the supply chain and creates a competitive edge in efficiency. Based on this reasoning, the following hypothesis is proposed:
H2: *DT improves SCE in CMCs by enhancing TDR.*

Process Optimization Pathway via OME

OME reflects a firm's ability to coordinate and allocate production resources effectively (Feng & Ali, 2024b). For listed manufacturing firms in China, the increasing scale and complexity of business operations have made traditional experience-based and hierarchical management approaches less effective. DT addresses this challenge by integrating systems such as Enterprise Resource Planning (ERP), Manufacturing Execution Systems (MES), and Supply Chain Management (SCM) (Feng & Ali, 2024a; Qureshi, 2022). These digital systems enable end-to-end management of human, financial, and material resources, thereby improving operational efficiency.

Enhanced operational efficiency can directly improve supply chain performance. This is achieved by reducing order processing time, optimizing production scheduling, and lowering inventory backlogs and logistics costs (He et al., 2024). In addition, data-driven lean management and process reengineering help firms identify and resolve supply chain bottlenecks and inefficiencies in a timely manner. This also improves the firm's ability to anticipate and respond to supply chain disruptions (Fu et al., 2024; Ivanov et al., 2019).

Management efficiency serves as a key link between internal operations and external supply networks. As such, it represents one of the critical channels through which DT enhances SCE in CMCs. Based on this reasoning, the following hypothesis is proposed:
H3: *DT improves SCE in listed Chinese manufacturing firms by enhancing OME.*

Research Design

Variable Definitions and Interpretations

Dependent Variable

This study uses SCE as the dependent variable, measured by inventory turnover. Inventory turnover reflects how quickly a company converts inventory into sales revenue and is widely used as a proxy for SCE (Areo, 2024; Chan et al., 2023). A higher turnover indicates lower inventory backlog and faster material flow, implying greater efficiency in inventory management, demand forecasting, and production scheduling (Prabha et al., 2024). Since inventory serves as a key link among suppliers, manufacturers, and customers, its turnover level directly affects the responsiveness and cost control of the entire supply chain. Therefore, it signals the level of coordination and agility across the supply chain. Moreover, inventory turnover offers strong data availability and comparability, enabling empirical analysis and benchmarking across firms and industries. As such, it is considered both a practical and representative indicator in theoretical and applied research.

Independent Variable

The independent variable, DT, follows the approach of Li (2025) and Liu et al. (2024), measured using the Wu Index (2021). This index captures the degree of DT by calculating the natural logarithm of the frequency count of digital-related keywords—such as *artificial intelligence*, *big data*, and *cloud computing*—appearing in firms' annual reports. This method effectively reflects the emphasis a firm place on digital technologies and has been widely adopted in empirical studies on digitalization due to its representativeness and operational feasibility.

Mediating Variables

This study introduces two mediating variables—technological TDR and OME—to explore the internal mechanisms through which DT affects SCE.

Technological R&D investment is measured by the TDR, calculated as the ratio of R&D expenditure to operating revenue (Ghazal et al., 2024; Jiang et al., 2024). This indicator reflects a firm's investment in innovation and product development, and indicates its capacity for knowledge accumulation and technological advancement.

OME is measured using the administrative expense ratio, defined as the ratio of administrative expenses to operating revenue. This variable captures a firm's efficiency in allocating resources and executing daily operations, and reflects its organizational management, cost control, and coordination capabilities (Maheshwari & Naik, 2024). A lower administrative expense ratio generally signals higher operational efficiency and is widely used as a financial indicator in performance-related studies.

Control Variables

To control for other factors that may influence SCE and enhance the accuracy and robustness of model estimation, this study includes a set of control variables following prior literature Ahmed et al.(2023)， Mansour et al. (2023)，Yang et al. (2025). These variables include firm size (size), firm age (age), leverage ratio (Lev), return on assets (roa), capital intensity (Cir), board size (Board), Tobin's Q (TobinQ), gross profit margin (Margin), and ownership concentration (top1). These controls account for differences in resource endowments, corporate governance, financial condition, and market performance, thereby reducing confounding effects related to strategic orientation, industry heterogeneity, and market fluctuations. This approach ensures a more accurate identification of the independent effect of DT on SCE and enhances the explanatory power and credibility of the empirical analysis. See Table 1.

Table 1
Variable Definitions

Variable Type	Variable Name	Symbol	Measurement Definition
Dependent Variable	Supply Chain Efficiency	SCE	In (Inventory Turnover + 1)
Independent Variable	Digital Transformation	DT	In (Total frequency of digital technology terms + 1)
Mediating Variable	R&D Intensity	TDR	In (Main Business Revenue / R&D Expenditure)
	Operational Management Efficiency	OME	In (Administrative Expenses / Operating Revenue)
Control Variable	Firm Size	size	In (Total Assets)
	Firm Age	age	Years since Initial Public Offering
	Leverage	Lev	Total Liabilities / Total Assets
	Return on Assets	roa	Net Profit / Total Assets
	Capital Intensity	Cir	Total Assets / Operating Revenue
	Board Size	Board	In (Number of Directors)
	Tobin's Q	TobinQ	Market Value / Replacement Cost of Capital
	Gross Margin	Margin	Gross Profit / Operating Revenue
	Ownership Concentration	top1	Shareholding Ratio of the Largest Shareholder

Sample Selection and Data Sources

This study selects A-share listed manufacturing firms in China from 2014 to 2023 as the research sample. The data are mainly obtained from the CSMAR database and company annual reports. To address potential outliers, the following data processing steps are performed using Stata 17: (1) firms labeled ST, *ST, and PT are excluded; (2) delisted firms are removed; (3) observations with missing key variables are dropped; (4) continuous variables are winsorized at the 1% level on both tails to mitigate the influence of extreme values. After processing, the final dataset contains 5,535 firm-year observations from 873 listed companies over the 10-year period.

Statistical Model

To examine the impact of DT on SCE, this study constructs a two-way fixed effects model as follows:

$$SCE_{it} = \alpha_0 + \alpha_1 DT_{it} + \sum Controls + ID_i + \sum Year + \varepsilon_{it} \qquad (1)$$

In the model (1), *i* denotes the firm and *t* represents the year. SCE_{it} refers to the SCE of firm *i* in year *t*. DT_{it} measures the degree of DT. Controls is a set of control variables.

DT_{it} and *Year* represent firm and year fixed effects, respectively. $\mathcal{E}_{it}$ is the random error term. α_0 is the intercept, and α_1 captures the estimated effect of DT on SCE. Equation (1) is designed to test Hypothesis H1.

To further explore the mechanism through which DT influences SCE and to test Hypotheses H2 and H3, the following mediation models are constructed:

$$M_{it} = \beta_0 + \beta_1 DT_{it} + \sum Controls + ID_i + \sum Year + \varepsilon_{it} \qquad (2)$$

$$\mathrm{SCE_{it}} = \theta_0 + \theta_1 \mathrm{DT_{it}} + \theta_2 \mathrm{M_{it}} + \sum \mathrm{Controls} + \mathrm{ID_i} + \sum \mathrm{Year} + \varepsilon_{it} \qquad (3)$$

M denotes the mediating variable in the relationship between DT and SCE. This includes technology development rate and OME. β_0 is the intercept, and β_1 represents the estimated effect of DT on the mediating variable. Other variables follow the same definitions as in the baseline model.

If β_1 and ϑ_2 are statistically significant, and ϑ_1 decreases after including *M*, this indicates the presence of a partial mediation effect. If ϑ_1 becomes statistically insignificant, it may suggest a full mediation effect.

Empirical Results

Descriptive Statistics

Table 2 reports the descriptive statistics. The sample includes 5,535 firm-year observations. The mean of SCE is 4.657 with a standard deviation of 9.891, ranging from 0.00612 to 471.7. This indicates wide variation in SCE across firms, suggesting that certain manufacturing firms still have substantial room for improvement.

The average value of DT is 2.113, with a minimum of 0 and a maximum of 5.159, implying that the overall level of DT among the sampled firms remains relatively low.

TDR has a standard deviation of 1.487, reflecting significant heterogeneity in TDR. The mean of OME is 0.0887 with a standard deviation of 0.176, showing smaller variability in operational efficiency across firms.

Other control variables also exhibit considerable dispersion, consistent with existing literature.

Table 2
Descriptive Statistics

Variable	N	Mean	SD	Min	Max
SCE	5535	4.657	9.891	0.00612	471.7
DT	5535	2.113	1.214	0	5.159
TDR	5535	0.0806	1.487	0.000134	109.1
OME	5535	0.0887	0.176	-0.111	11.79
size	5535	22.35	1.198	17.64	27.62
age	5535	2.136	0.783	0	3.497
Lev	5535	0.422	0.188	0.0140	2.290
roa	5535	0.0356	0.0850	-2.071	0.759
Cir	5535	2.367	8.894	0.268	710.5
Board	5535	8.070	1.478	0	17
TobinQ	5535	2.263	2.271	0.681	122.2
Margin	5535	0.301	0.168	-0.978	0.994
top1	5535	31.89	13.97	1.840	89.09
Growth	5535	0.535	14.07	-3.095	1145

Baseline Regression Results

Table 3 presents the panel regression results using a two-way fixed effects model. Column (1) reports the regression without controls; Column (2) includes control variables; Column (3) accounts for firm and year fixed effects; and Column (4) adds both controls and fixed effects, corresponding to Equation (1). The analysis progresses from a basic specification to a fully adjusted model to enhance explanatory power and robustness.

In Column (1), DT shows a coefficient of 0.196, significant at the 5% level, indicating a positive association between DT and SCE. After including control variables in Column (2), the coefficient rises to 0.308 and becomes significant at the 1% level, suggesting that DT's effect strengthens when accounting for firm characteristics and governance.

Column (3), which introduces firm and year fixed effects, reports a DT coefficient of 0.324 (significant at 5%), confirming the robustness of the DT–SCE relationship even after accounting for unobserved heterogeneity. In the fully specified model in Column (4), DT remains positively associated with SCE (coefficient = 0.113, significant at the 5% level), validating the independent effect of DT on supply chain performance.

Among the controls, size, Lev, roa, Cir, TobinQ, and Growth show significant associations in several specifications. Notably, roa and Cir consistently exhibit positive effects, indicating that firms with higher profitability and capital efficiency tend to have better SCE. Margin is negatively associated with SCE across all models, potentially reflecting that firms with higher gross margins may place less emphasis on inventory management, leading to lower turnover efficiency.

The model's overall fit improves progressively with the inclusion of control variables and fixed effects. In Column (1), the adjusted R^2 is 0, indicating that DT alone explains little

variance in SCE. After adding controls (Column 2), the adjusted R^2 increases to 0.114. Controlling for fixed effects (Column 3) raises it further to 0.596. In the fully specified model (Column 4), the adjusted R^2 reaches 0.950, suggesting that the model effectively explains the variation in SCE and demonstrates strong goodness-of-fit.
Thus, H1 is supported.

Table 1
Baseline Regression Results

	(1)	(2)	(3)	(4)
	SCE	SCE	SCE	SCE
DT	0.196**	0.308***	0.324**	0.113**
	(2.1135)	(3.4253)	(2.4112)	(2.2541)
size		0.422***		0.177*
		(3.1734)		(1.6596)
age		0.064		-0.260
		(0.3707)		(-1.3457)
Lev		2.452***		-0.533
		(3.1531)		(-1.4086)
roa		9.316***		3.175***
		(6.2421)		(6.3903)
Cir		0.141***		0.200***
		(5.4985)		(27.6484)
Board		0.009		0.054
		(0.1198)		(1.3612)
TobinQ		0.927***		0.006
		(20.2181)		(0.1806)
Margin		-8.133***		-4.483***
		(-10.8878)		(-7.5184)
top1		0.014*		-0.001
		(1.6666)		(-0.1621)
Growth		0.189***		0.025***
		(10.3050)		(5.1198)
_cons	4.243***	-7.591***	8.053	9.173***
	(18.7860)	(-2.8348)	(1.2775)	(3.2837)
Year fe	No	No	Yes	Yes
code fe	No	No	Yes	Yes
N	5535	5535	5535	5535
r2_a	0.000	0.114	0.596	0.950

t statistics in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Robustness and Endogeneity Tests

Robustness Test

Alternative Dependent Variable

Table 2

Baseline Regression Results with Alternative Dependent Variable

	(1) BC	(2) BC
DT	-4.604**	-5.108**
	(-2.1209)	(-2.0193)
Controls	No	Yes
_cons	280.445***	397.724***
	(3.8842)	(3.1503)
Year fe	Yes	Yes
code fe	Yes	Yes
N	5535	5535
r2_a	0.981	0.866

t statistics in parentheses

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

To test robustness, an alternative proxy for SCE is employed. Following prior literature (Ferrari, 2023; Q. Wang et al., 2023), Business Cycle (BC) is used to capture SCE. Table 4 reports the regression results.

In Column (1), without controls, the DT coefficient is –4.604. In Column (2), after adding control variables, the coefficient is –5.108 and remains significant at the 5% level. The negative sign indicates that DT shortens the BC, implying faster supply chain responses and enhanced flexibility. These findings confirm that DT improves SCE, validating the robustness of the baseline results.

Alternative Independent Variable

Table 3

Baseline Regression Results with Alternative Independent Variable

	(1) SCE	(2) SCE
DTV	1.241**	0.671**
	(2.4681)	(2.2048)
Controls	No	Yes
_cons	7.815	1.551
	(1.1681)	(0.3215)
Year fe	Yes	Yes
code fe	Yes	Yes
N	5535	5535
r2_a	0.408	0.740

t statistics in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

To further verify the robustness of the findings, this study adopts an alternative independent variable—Digital Transformation Velocity (DTV)—following the approach of Sun et al. (2024). DTV measures the rate of change in the frequency of digital technology terms over time, capturing the dynamic evolution of DT. It emphasizes the speed and rhythm of digital adoption, thereby reflecting firms' behavioral characteristics more comprehensively during the transformation process.

Table 5 presents the regression results. In Column (1), without controls, the coefficient of DTV is 1.241. In Column (2), after including controls, the coefficient is 0.671. Both coefficients are positive and significant at the 5% level, indicating that a higher DTV enhances SCE. These results confirm that regardless of the DT measurement used, DT contributes positively to SCE, thus supporting the robustness of the study's conclusions.

Endogeneity Test

Table 4

Endogeneity Test Results

	(1)	(2)	（3）	（4）
	DT	SCE	DT	SCE
BOC	0.001***			
	(6.5265)			
DOU			0.002***	
			(8.0392)	
DT		1.710**		0.1959**
		(1.7612)		(2.11)
Controls	Yes	Yes	Yes	Yes
Year fe	Yes	Yes	Yes	Yes
code fe	Yes	Yes	Yes	Yes
N	5535	5535	5535	5535
r2_a	0.0241		0.0239	
Kleibergen-Paap rk LM	67.278***			
Cragg-Donald Wald F	35.154			
Kleibergen-Paap rk Wald F	34.254			
10% maximal IV size	19.93			
Hansen J (P)	0.061 (0.8042)			

*t statistics in parentheses * p < 0.1, ** p < 0.05, *** p < 0.01*

This study applies the instrumental variable approach to address potential endogeneity in the model. Two instrumental variables are adopted: breadth of coverage (BOC) and depth of use (DOU). BOC reflects the business scope and stakeholder reach of DT, while DOU captures the extent to which digital tools are utilized within that scope. Both are closely associated with the implementation level of DT and are thus appropriate instruments.

Two-stage least squares (2SLS) regression results are reported in Table 6. The Kleibergen-Paap rk LM statistic is 67.278, significant at the 1% level, indicating no under-identification problem. Cragg-Donald Wald F and Kleibergen-Paap rk Wald F statistics are 35.154 and 34.254, respectively—both exceeding the critical value of 19.93 at the 10% level—indicating no weak instrument problem. The Hansen J statistic is 0.061 (p = 0.8042), suggesting no over-identification issue. Thus, the selected instrumental variable s are valid.

In Columns (1) and (3), the coefficients of DT on SCE are 0.001 and 0.002, respectively, both significant at the 1% level. This confirms that DT is strongly correlated with BOC and DOU, validating the IVs. Columns (2) and (4) show the coefficients of BOC and DOU on DT as 1.710 and 0.1959, respectively, significant at the 5% level. After addressing endogeneity, the positive effect of DT on SCE remains, supporting the robustness of the findings.

Mediation Effect Test
Table 7 presents the mediation analysis results, examining the paths from DT to SCE through TDR and OME. The three-step regression approach is applied. All regressions control for firm and year fixed effects. The sample size is 5,535, and model fit is generally high. Columns (2) and (4) correspond to Equation (2), and Column (3) and (4) corresponds to Equation (3).

Table 5
Mediation Effect Test Results

	(1) SCE	(2) TDR	(3) SCE	(4) OME	(5) SCE
DT	0.113** (-2.2541)	0.370*** (-3.3403)	0.107** (-2.3319)	0.342** (-2.2231)	0.109** (-2.1719)
TDR			3.492*** (-28.3044)		
OME					0.008*** (-3.9877)
Controls	Yes	Yes	Yes	Yes	Yes
_cons	9.211*** (-3.3054)	11.597** (-2.1293)	9.173*** (-3.2837)	193.727*** (-25.1973)	8.021*** (-2.7037)
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
N	5535	5535	5535	5535	5535
R^2_adj	0.95	0.891	0.943	0.994	0.95

TDR Path
As shown in Column (1) of Table 7, DT has a direct positive effect on SCE, with a coefficient of 0.113 significant at the 5% level (t = –2.2541). Column (2) confirms that DT also positively affects TDR, with a coefficient of 0.370 ($p < 0.01$), indicating that DT significantly promotes firms' investment in R&D. In Column (3), after including TDR, its coefficient on SCE is 3.492, significant at the 1% level (t = –28.3044), while the coefficient of DT slightly decreases to 0.107 but remains significant at the 5% level. This suggests that TDR plays a partial mediating role between DT and SCE, meaning DT enhances SCE partly by increasing R&D investment.

In practice, as industries move toward higher value-added activities, manufacturing firms are under pressure to improve quality and efficiency. Integrating digital systems with core technology R&D has become essential for enabling intelligent products and flexible production. Under the ongoing national policy initiative *Cloud Adoption, Data Utilization*, and *Intelligence Empowerment*, firms are increasingly investing in smart equipment, predictive algorithms, and data-driven product development. These efforts not only strengthen technical capacity but also enhance supply chain planning, accuracy, and agility—leading to shorter production cycles and faster delivery. Several lubricant manufacturing companies have integrated open innovation (OI) with advanced technology R\&D to build smart supply

chains. By applying multi-agent simulation platforms, they have not only improved supply chain transparency and efficiency but also enhanced agility and predictability across the entire chain(M. S. Ahmed et al., 2025).
Therefore, H2 is supported: DT improves SCE indirectly by increasing TDR.

OME Path
Column (4) shows that DT positively and significantly affects OME, with a coefficient of 0.342 ($p < 0.05$), indicating that DT contributes to improving firms' management efficiency. In Column (5), OME has a positive effect on SCE (coefficient = 0.008, $p < 0.01$), while the direct effect of DT on SCE remains significant (coefficient = 0.109). This suggests that OME partially mediates the relationship between DT and SCE, confirming that DT indirectly improves SCE through enhanced management efficiency.

Regarding OME, DT enables the visualization and intelligence of supply chain operations in manufacturing firms. Through IoT technologies, firms can monitor real-time information on raw material inventory, production progress, and logistics status. This allows for timely adjustments in production and logistics, reducing risks of overstock or stockouts. For example, Siemens uses its industrial cloud platform to track global material flows and equipment conditions in real time, allowing dynamic alignment of production schedules and inventory allocation while eliminating traditional supply chain information gaps.

DT also optimizes internal management processes. By implementing ERP and CRM systems, firms can enhance information sharing and collaboration across departments. These improvements support the validation of H3: DT enhances SCE by improving OME.

Research Conclusions and Implications
Main Findings
Using panel data from A-share listed manufacturing firms in China from 2014 to 2023, this study investigates the impact of DT on SCE and explores the mediating mechanisms through TDR and OME. The key findings are as follows:

1. DT significantly improves SCE among CMCs. Baseline regression results show a robust and significant positive relationship between DT and SCE, regardless of whether firm and year fixed effects are included. This indicates that DT enhances coordination and responsiveness across supply chain processes.
2. TDR mediates the effect of DT on SCE. DT enhances the efficiency of R&D data processing and collaborative innovation, leading to modular product design and localized core component production. These improvements increase upstream supply chain stability and flexibility, thereby enhancing overall SCE. This supports H2.
3. OME also acts as a mediator in the DT–SCE relationship. Firms leverage ERP, MES, and other digital systems to optimize production scheduling and logistics operations. These technologies enhance process precision and responsiveness, improve inventory turnover, and increase resource utilization efficiency. This supports H3.
4. Robustness and endogeneity tests confirm the reliability of the above findings. Alternative measurements for both the dependent and independent variables yield consistent results. Instrumental variable regressions using BOC and DOU also confirm the positive effect of DT on SCE, indicating strong robustness and credibility of the conclusions.

Research Implications

1. Manufacturing firms should position DT as a core strategy to enhance SCE, continuously integrating digital systems with operational processes.
2. TDR serves as a key mediating pathway for improving SCE. Firms should increase investment in digital R&D capabilities to advance autonomy and intelligence in critical supply chain segments.
3. The improvement of OME depends on digital infrastructure. Firms are advised to strengthen the implementation of ERP, MES, and related systems to optimize inventory, production, and logistics processes.
4. The government should intensify support for DT in manufacturing by refining incentive policies and fostering collaborative innovation across the supply chain, thereby enhancing overall resilience and efficiency.

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