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Mechanisms of Supply Chain Digitalization in Advancing High-Quality Development in Manufacturing Firms

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Abstract: Supply chain digitalization (SCD) has been recognized as a critical enabler of high-quality development in the manufacturing sector. To explore its influence mechanisms, an SCD indicator was constructed through textual analysis of corporate disclosures by Chinese manufacturing firms listed on the Shanghai and Shenzhen A-share markets from 2008 to 2022. Based on the theoretical lens of supply chain integration, the impact of SCD on high-quality development was empirically examined. The findings indicate that SCD significantly promotes high-quality development across manufacturing firms. Further analysis revealed that this relationship is positively mediated by two core mechanisms: supply chain collaborative innovation and the advancement of supply chain finance (SCF). These mediating effects were found to be strengthened under conditions of heightened environmental dynamism, underscoring the adaptive value of digital supply chain capabilities in volatile contexts. Heterogeneity analysis demonstrated that the positive effects of SCD are more pronounced in non-state-owned enterprises, firms in growth or decline stages, and those characterized by low levels of resource slack. Additionally, the long-term economic consequences of SCD were evaluated, and it was observed that enhanced digitalization contributes to the stable growth of firms' long-term value by reinforcing their high-quality development trajectories. By clarifying the pathways through which SCD influences development outcomes, this study offers empirical evidence that enriches the existing body of literature on digital transformation within supply chains. Moreover, practical implications are provided for policy formulation and strategic decision-making aimed at fostering digitally integrated, innovation-driven, and financially resilient manufacturing ecosystems.

Keywords: Supply chain digitalization (SCD); High-quality development; Manufacturing firms; Supply chain collaborative innovation; Supply chain finance (SCF); Supply chain integration

1 Introduction

Numerous companies have recently recognized that applying digital technologies such as artificial intelligence (AI), big data, blockchain and the Internet of Things in supply chain management enhances visualization and intelligence, which can serve better resource distribution and more efficient production processes [1]. SCD has gradually become a critical strategy for improving the quality and efficiency of manufacturing processes [2]. Facing uncertainty in the market, the manufacturing firms need to promote SCD to enhance synergy and cooperation among supply chain segments [3]. While existing studies have primarily focused on operational and cost efficiency [4], few have systematically examined the underlying mechanisms through which SCD enables high-quality development—particularly in dynamic, uncertain environments. To address this theoretical gap, this study draws on four complementary theoretical perspectives: dynamic capability theory, resource-based theory, financial intermediation theory, and organizational adaptation theory. These frameworks help explain how SCD strengthens firms' responsiveness, resource integration capabilities, financing efficiency, and adaptability to environmental uncertainty—key mechanisms that enable high-quality development in volatile contexts.

Researchers have focused on how companies can enhance their competitiveness through SCD, debating its actual value and economic benefits. Several studies indicate that SCD can significantly increase firm value and economic benefits. For instance, SCD improves performance, market responsiveness, and customer satisfaction [5]. Furthermore, firms can achieve more efficient operation management and flexible supply chain responsiveness by leveraging digital technologies [6]. For example, their use in procurement and supply chain processes helps lower inventory levels and costs, ultimately boosting financial performance [7–9]. In addition, SCD can improve information transparency and enhance the supply chain's synergy effect, quickly adapting to the variations of environment [10, 11]. However, researchers have also considered the potential risks of SCD. First, cybersecurity vulnerabilities have emerged as a core concern. As firms increasingly integrate digital platforms, sensors, and data-sharing systems across supply chains, the attack surface for cyber threats expands significantly. Melnyk et al. [12] showed that digital interconnectedness increases the risk of data breaches, system sabotage, and cascading operational disruptions, which may be difficult to contain in real time. Moreover, digital twins and real-time visibility platforms, while valuable for agility, can become critical points of failure when targeted by cyberattacks [13, 14]. Second, the issue of technological dependence and lock-in effects is becoming more pronounced. Birkel and Wehrle [6] pointed out that manufacturing firms increasingly rely on third-party service providers (e.g., SaaS platforms, cloud infrastructure, proprietary Application Programming Interfaces (APIs) for digital supply chain functions. This reliance can reduce firms' autonomy and agility, especially when faced with technology changes, vendor failures, or cross-border data regulations [15]. Third, while digital technologies such as AI and big data analytics enhance supply chain responsiveness and decision-making, recent discussions have highlighted the potential risks of opaque algorithms and lack of governance mechanisms. As these systems are increasingly deployed in procurement, logistics, and finance, concerns around fairness, accountability, and decision bias are emerging. In particular, over-reliance on automated systems during dynamic or crisis periods may erode firms' adaptive capacity—ironically undermining the resilience that SCD aims to build [16, 17]. Fourth, some studies have examined the structural vulnerabilities and systemic fragility introduced by SCD. Hosseini and Ivanov [18] demonstrated that digitalized supply chains, while efficient, tend to be more tightly coupled and thus more susceptible to ripple effects when disruptions occur. Similarly, Ivanov and Dolgui [19] emphasized that in digitalized and globally integrated supply chains, failures in one node—such as a data platform outage, API error, or supplier system breach—can propagate rapidly across the network, escalating firm-level risks into system-wide instability. These concerns are particularly salient in emerging economies, where digital governance capacity and institutional support may be insufficient. As such, recent literature advocates for integrating risk awareness and resilience thinking into digital transformation strategies, emphasizing that the benefits of SCD must be pursued in parallel with robust cybersecurity architecture, governance mechanisms, and organizational adaptability.

Although existing literature has provided valuable insights into both the benefits and risks of SCD, current findings remain fragmented and largely conceptual. Most studies are theoretical in nature or rely on case-based approaches, with limited empirical evidence—particularly at the micro-firm level [20]. Although to some extent, researchers have adopted the empirical analysis methods of building simulation models with questionnaires [7–11], and constructing quasi-natural experimental dummy variables [21], they remain confined to quantitative SCD evaluation methods, which can only provide limited support for the empirical study of micro effects. To address these research gaps, this study employs a micro-data analytical framework to explore whether and how SCD contributes to the high-quality development of manufacturing firms. Specifically, the study adopts a text mining method based on Term Frequency-Inverse Document Frequency (TF-IDF) to capture firm-level digitalization activity, and further investigates two critical mediating channels—supply chain collaborative innovation and financial support. Accordingly, the following key research questions are posed: a) Can SCD promote high-quality development of manufacturing firms? b) Through which channels does SCD affect such development? c) Do different categories of firms differ significantly? d) Does SCD generate economic consequences that promote long-term development and stable development of manufacturing firms? The present research offers several significant contributions. First, it broadens the analytical scope of SCD by incorporating perspectives beyond digital innovation to include supply chain integration and its role in advancing firm quality development. While prior studies primarily concentrate on digital transformation, the digital economy, and industrial intelligence in relation to manufacturing firms, this study extends the empirical inquiry into SCD's influence from a supply chain viewpoint. Second, it develops an integrated analytical model that embeds supply chain collaborative innovation and SCF into the mechanism through which SCD promotes the high-quality development of manufacturing firms. Finally, it fills the research gap regarding empirical methods and quantitative indicators in SCD research. The TF-IDF method was used to measure the SCD indicator from market and technology strategy-oriented feature words in this analysis.

2 Theoretical Analysis and Research Hypotheses

2.1 Mechanisms of Direct Impact of SCD on Manufacturing Quality Development

According to dynamic capability theory, SCD enables firms to adapt to environmental uncertainty by enhancing responsiveness, flexibility, and supply chain coordination. To address these challenges and opportunities, more and more organizations are turning to digital supply chain management to boost operational efficiency, cut costs, and improve product and service standards. By integrating advanced technologies, SCD helps improve automation and information sharing, thereby strengthening supply chain agility and firms' capacity to respond to market shifts [22]. For example, using real-time data for monitoring and analytics can optimize inventory management along with production planning, reducing surplus or shortage situations to improve resource utilization efficiency [2]. Kache and Seuring [23] reported that companies, by leveraging real-time monitoring and analytics, are able to foresee possible supply chain interruptions and production-related risks. These predictive risk management capabilities enable companies to maintain stable production and product quality, thereby enhancing market competitiveness. In addition, SCD improves transparency and coordination across the supply chain, allowing firms to better align internal and external resources [24], improving their operational efficiency. SCD also improves product innovation and customer experience, increases supply chain sustainability, and contributes to moving manufacturing firms towards the "smile curve" [5].

SCD is both a tool to improve manufacturing firms' operational efficiency and a measure to help them transition from single production to integrated services [25]. Traditional supply chain cooperation models are based on transactional relationships and economic interests, with "data silos" and barriers to cooperation between individual segments. However, digital technology breaks down barriers between producers and consumers, suppliers, manufacturers, and distributors, enabling upstream and downstream supply chain firms to participate, through digital platforms, in the process of product design, production, and sales [26]. This type of real-time data exchange and collaborative engagement enables supply chain partners to better coordinate efforts, enhancing overall efficiency and adaptability across the supply chain, which not only promotes continuous product improvement and innovation among firms but also hastens their intelligent upgrading and ecological development. Simultaneously, digital technology provides more flexible financial tools within the supply chain, including options like order, raw material, and receivables-based financing, respectively. Financing promotes the transformation of their products and services into high-quality, high value-added outputs [19]. Finally, SCD promotes sustainability in manufacturing; by reducing energy consumption and waste generation and implementing more environmentally friendly operational strategies, SCD can help reduce negative environmental impacts and contribute to the greening of the manufacturing sector [27]. Nevertheless, SCD's positive impact may be contingent upon adequate digital governance and cyber-resilience capabilities. Without robust data protection, interoperability protocols, or crisis response mechanisms, digital integration may expose firms to cascading risks, thus offsetting the intended benefits of high-quality development [28]. Drawing upon the above analysis, the hypothesis below was proposed:

Hypothesis 1: SCD has a significant impact on the high-quality development of manufacturing firms.

2.2 SCD, Supply Chain Collaborative Innovation and High-Quality Development of Manufacturing Firms

Resource-based theory suggests that firms' capacity to develop irreplaceable strategic assets is a fundamental determinant in maintaining competitive advantage and achieving sustainable development. Further, supply chain collaborative innovation ($CInnov$) helps innovation agents to break traditional boundaries, thus enhancing the value and core competitiveness of firms through effective integration and sharing of key resources [29].

Existing literature reveals how SCD promotes innovation collaboration from the following three perspectives: trust, resource, and communication. First, SCD enhances trust between upstream and downstream supply chain firms by improving network layout and optimizing channel integration, facilitating the formation of a more efficient and transparent supply chain management model [30]. This trust-based network enables firms to more efficiently coordinate their research and development (R and D) activities, thus improving cooperation and innovation [31]. Second, firms limited by insufficient resources during the growth process find that realizing sustainable development during the lifecycle leap is more challenging [32]. SCD enables them to integrate internal and external resources, enhancing external collaboration networks and constructing digital supply chain systems based on key technologies, allowing firms to optimize resource use and maximize value [33]. Third, Molina-Morales et al. [34] explored how geographic proximity between cooperating firms affects their collaborative innovation. SCD creates collaborative network accounts for suppliers and customers and relies on the interconnectivity and integration advantages of the supply chain to help upstream and downstream cooperate, incentivizing both collaborative and sustainable innovation [24]. Meanwhile, Wan et al. [35] pointed out that industrial integration can improve collaborative innovation among industry firms, thus promoting high-quality manufacturing development. Drawing upon the above analysis, the hypothesis below was proposed:

Hypothesis 2: SCD facilitates supply chain collaborative innovation, which in turn promotes the high-quality development of manufacturing firms.

2.3 SCD, SCF and High-Quality Development of Manufacturing Firms

Financial intermediation theory suggests that digital financial systems reduce information asymmetry and improve capital allocation efficiency by enhancing trust and transparency among economic agents. In this context, SCF serves as a key digital-enabled financial mechanism that facilitates the flow of capital, logistics, and information across supply chain participants, especially when traditional financing channels are constrained [36]. Empowered by SCD, SCF leverages technologies such as blockchain, big data, and platform-based credit systems to strengthen credit evaluation and provide Small and Medium-sized Enterprises (SMEs) with more accessible and cost-effective financing channels [37].

In SCF, the application of digital technology, especially financial technology (FinTech), has altered traditional financing. A robust FinTech platform can help build trust between borrowers and lenders by reducing the asymmetry of information. Moreover, blockchain technology can create more secure SCF, mitigating disruption risks and lowering capital costs [38]. Stable relationships within the supply chain can improve credit accessibility, thus stabilizing corporate earnings and ultimately increasing corporate value [39]. In addition, due to the innovative integration of digital technology, SCF outperforms traditional financial services regarding cost, operational efficiency, and risk control; consequently, customers find more supplier finance available to realize high-quality development [40]. Finally, SCD also helps manufacturing firms adapt to new markets and technologies. By providing flexible financing options and improved market analysis tools, digitized SCF helps firms respond quickly to marketing changes and new business opportunities; this agility enhances competitive advantage and rapid development [41]. Overall, SCF not only reforms the technical aspects but also reduces the cost of corporate debt, thus promoting sustainable development and long-term competitiveness of manufacturing firms through the use of supply chain-oriented financial tools. Drawing upon the above analysis, the hypothesis below was proposed:

Hypothesis 3: SCD facilitates SCF, which in turn contributes to the high-quality development of manufacturing firms.

2.4 Moderating Role of Environmental Dynamics

Organizational adaptation theory emphasizes how firms must adjust to variations in external conditions. Environmental conditions along with firm-specific traits differ significantly; one of the key characteristics is environmental dynamism [42]. It describes the complexity and uncertainty of the external environment, which significantly impact operations and strategic decisions. Supply chain collaborative innovation and SCF become important tools for adaptation.

Supply chain collaborative innovation involves cross-enterprise information sharing, resource integration, and joint decision-making. All help firms accelerate R and D innovation, thereby optimizing operations [43]. Thus, in a highly dynamic environment, firms tend to adopt digital technologies to strengthen cooperation across the supply chain, aiming to sustain relatively stable collaborative innovation that meets customer expectations [44].

SCF helps decrease financial risks and uncertainties through efficient fund management and innovative finance, such as supply chain insurance and Fintech services [45]. Especially in highly uncertain market environments, innovative solutions in SCF become particularly important for firms to maintain stable capital flows and flexible risk management strategies to retain competitive advantages [37, 46].

Therefore, environmental dynamics may reveal that supply chain co-innovation and SCF are key links between SCD and high-quality development of manufacturing firms. Drawing upon the above analysis, the hypotheses below were proposed:

Hypothesis 4: Environmental dynamism positively moderates how supply chain collaborative innovation mediates the link between SCD and high-quality development of manufacturing firms.

Hypothesis 5: Environmental dynamism positively moderates how SCF mediates the link between SCD and high-quality development of manufacturing firms.

Figure 1 illustrates the model constructed from the proposed hypotheses.

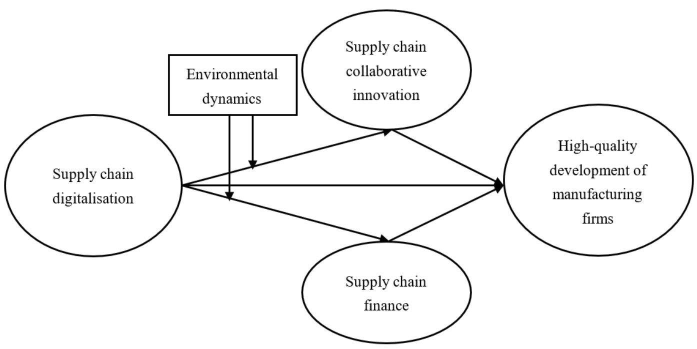

Figure 1. Research model

3 Research Design

3.1 Data

This study focuses on A-share manufacturing firms listed in Shanghai and Shenzhen between 2008 and 2022. To ensure research quality, the samples were filtered based on the following criteria: (a) firms marked ST or delisted during the sample period were excluded; (b) firms with missing key data or abnormal financial conditions were excluded; (c) all continuous variables were winsorized at the 1st and 99th percentiles. After applying these filters, 21,321 firm-year observations were obtained. Basic enterprise data were sourced from the China Stock Market and Accounting Research (CSMAR) and China Research Data Services (CNRDS) databases, while annual report texts were collected from the Juchao Information Network.

3.2 Variables

3.2.1 Explained variable (HQD_LP)

The variable HQD_LP reflects the high-quality development level of manufacturing firms. Jia et al. [47] adopted total factor productivity (TFP) to measure the high-quality development level of manufacturing firms. TFP essentially reflects production efficiency and captures the contribution of non-input factors such as technological progress and institutional improvement to output growth. Currently, the measurement of TFP primarily relies on the Levinsohn-Petrin (LP) method [48] and the Olley-Pakes (OP) method [49], as these approaches effectively address the issue of selection bias arising from the endogeneity of input choices. Accordingly, TFP was computed using both the LP and OP methods, which serve as the basis for constructing the proxy variables HQD_LP and HQD_OP, respectively, to indicate the high-quality development level of manufacturing firms. Considering that this study uses micro-level data of manufacturing firms and the LP method has advantages in reducing sample loss, TFP estimated by the LP method was employed as the benchmark proxy variable in the baseline regressions, while the OP method was applied in robustness tests for cross-validation. The formula used to compute TFP is shown as follows:

$$\ln Y_{it} = \alpha \ln L_{it} + \beta \ln K_{it} + \gamma \ln M_{it} + \varepsilon_{it} \tag{1}$$

where, i and t denote the firm and the year, respectively; Y denotes firm output, measured by operating revenue; L represents labor input, calculated based on employee count; K indicates capital stock, measured by net fixed assets; M serves as a proxy variable, defined by intermediate goods input in the LP method and current investment in the OP method; and is the random disturbance term, capturing the high-quality development status of manufacturing firms. In addition, all financial indicators were obtained from the CSMAR database.

3.2.2 Explanatory variable (SCD)

Following the integrated digital strategy framework proposed by Ho et al. [50], which emphasizes aligning technology with market demands to digitally transform supply chains, a measurement system for the level of SCD among manufacturing firms was constructed based on a strategy-oriented perspective. This approach incorporates theoretical insights from Ho et al. [50], national policy documents, and textual content from listed firms' annual reports, combining both market- and technology-oriented dimensions. Compared to existing approaches that rely on policy-based dummy variables, the proposed measure focuses more on capturing the actual digital development at the firm level. It enables us to reflect variations in the degree and evolution of SCD across firms, providing a more continuous and comparable indicator, thereby improving the precision and explanatory power of SCD measurement. The construction process is as follows:

First, drawing upon the Statistical Classification of the Digital Economy and Its Core Industries (2021) released by the National Bureau of Statistics of China, Jieba segmentation in Python was applied to extract 144 digital technology–related policy-guided keywords, including representative terms such as "Internet of Things," "Industrial Internet," "big data," "blockchain," and "intelligent manufacturing." These keywords reflect critical focus areas of SCD from the perspectives of industrial policy and technological evolution.

Second, existing digital transformation indicators in manufacturing firms [51] were referred to and the Management Discussion and Analysis sections of annual reports from Chinese A-share listed manufacturing firms were used as the data source. The text content was cleaned to remove stop words, industry clichés, and non-informative expressions, resulting in a standardized text corpus. Using Jieba segmentation, statements related to digital technology were extracted, ultimately identifying 161 SCD–related feature words.

Third, these 161 feature words were categorized into five sub-dimensions: four market-oriented dimensions—logistics flow, product flow, information flow, and capital flow—and one technology-oriented dimension. Then the term frequency (TF) values for each dimension were computed.

In addition, to address the common problem of overestimating the weight of frequently used terms and underestimating that of key features in TF calculations, the TF-IDF algorithm was adopted to refine the SCD measurement method. Compared to traditional TF values, the TF-IDF approach reduces bias toward common terms and enhances the representativeness and sensitivity of the indicator, making it particularly suitable for quantifying digitalization using structured lexicons and semi-structured texts (e.g., annual reports). Furthermore, TF-IDF-weighted scores were calculated for each dimension, and the final SCD indicator was constructed by multiplying the market-oriented TF-IDF values with those of the technology-oriented dimension and summing the results. The detailed calculation is shown in Eqs. (2)–(4).

$$TF-IDE_{it} = \frac{n_{it}}{N_{it}} \times \log\left(\frac{M_t}{m_t+1}\right) \tag{2}$$

$$SCD\_N_{it} = SCD\_n_{it} \times SCD\_j_{it} \tag{3}$$

$$SCD_{it} = \sum_{N=1}^{4} SCD\_N_{it} \tag{4}$$

where, n indicates the frequency of the feature word; N denotes the total number of valid words found in firm's annual report for year; M refers to the overall count of annual reports for year; m indicates how many reports contain the word n; SCD_n (n $= 1, 2, 3, 4$) reflects the TF-IDF values associated with market-related keywords from logistics, product, information, and capital flows; SCD_j captures the TF-IDF score of technology-oriented terms. In addition, SCD_N (N $= 1, 2, 3, 4$) quantifies the degree of digitalization for the four aforementioned flows, while SCD measures the aggregate digitalization degree of the supply chain. For the convenience of reading, SCD_N is scaled by multiplying the original value by 100.

3.2.3 Control variables

The control variables in this study mainly capture firms' fundamental conditions, intrinsic traits, and financial characteristics such as firm size ($Size$, log of total employment), firm age (Age, calculated as the current year minus founding year, plus one before log transformation), financial leverage (Lev, total liabilities to total assets), profitability (Roa, net profit over total assets), growth ($Growth$, annual change in operating income), intangible assets ratio ($Intang$, net intangible assets to total assets), cashflow ratio ($Cashflow$, operating cash flow relative to operating income), duality ($Duality$, equals 1 if the CEO also serves as the Chairman, 0 otherwise), independent director ratio ($Indep$, share of independent directors on the board), ownership concentration ($Top10$, equity percentage held by the top 10 shareholders), firm and year fixed effects, and other relevant controls.

3.3 Model Setting

To examine how SCD influences the high-quality advancement of manufacturing firms, the following model was constructed:

$$HQD\_LP_{it} = \alpha_0 + \alpha_1 SCD_{it} + \alpha_2 X_{it} + u_i + \delta_t + \varepsilon_{it} \tag{5}$$

where, HQD_LP reflects the high-quality development level of manufacturing firms; SCD captures the degree of SCD; X comprises the set of control variables; u and δ denote firm and time fixed effects; and ε represents the stochastic error term. If the coefficient α_1 in Eq. (5) is significantly positive, it indicates that Hypothesis 1 is supported.

4 Empirical Analysis

4.1 Descriptive Analysis

As presented in Table 1, the average HQD_LP is 14.165, accompanied by a standard deviation of 0.860, with observed values ranging from 11.687 to 17.782. These results indicate that high-quality development levels among firms differ significantly, suggesting substantial development potential in China's manufacturing sector. SCD exhibits a mean of 0.016 and a standard deviation of 0.059, approximately four times the mean, and only 1.6% of the sampled firms have engaged in SCD. These results suggest considerable variation in SCD across firms.

4.2 Benchmark Model and Results

The baseline regression findings are presented in Table 2. Columns (1) and (2) display the outcomes without and with control variables, respectively. The estimated coefficients of SCD remain statistically significant at the 1% and 5% levels, respectively. Notably, the inclusion of control variables reduces the estimated coefficient of SCD, but its significance remains, indicating that SCD's positive effect remains robust even after accounting for other influencing factors. In terms of economic significance, taking column (2) as an example, a one-standard-deviation rise in SCD corresponds to an approximate increase of 0.009 ($\approx 0.148 \times 0.860/14.165$) in high-quality development. While the absolute value may appear modest, it reflects a meaningful improvement in firm-level performance quality attributable to digital transformation. Even marginal enhancements in high-quality development can translate into considerable competitive advantages over time, especially in sectors where supply chain efficiency and innovation responsiveness are critical. Thus, Hypothesis 1 is empirically confirmed.

Table 1. Statistical results

Variables	Samples	Mean	Std. Dev.	Median	Min	Max
HQD_LP	21321	14.165	0.860	14.086	11.687	17.782
SCD	21321	0.016	0.059	0.001	0.000	0.711
$CInnov$	21321	0.687	1.121	0.000	0.000	4.860
SCF	21321	0.234	0.423	0.000	0.000	1.000
EN	15004	0.278	0.199	0.231	0.013	2.222
$Size$	21321	7.686	1.113	7.594	5.371	10.701
Age	21321	2.870	0.342	2.890	1.792	3.497
Lev	21321	0.391	0.191	0.384	0.053	0.837
Roa	21321	0.045	0.058	0.043	-0.182	0.211
$Growth$	21321	0.144	0.280	0.110	-0.462	1.337
$Intang$	21321	0.044	0.032	0.037	0.002	0.191
$Cashflow$	21321	0.090	0.129	0.085	-0.325	0.475
$Duality$	21321	0.306	0.461	0.000	0.000	1.000
$Indep$	21321	0.374	0.053	0.333	0.333	0.571
$Top10$	21321	0.593	0.148	0.602	0.245	0.896

Note: "Std. Dev." indicates the standard deviation.

Table 2. Regression results of SCD and HQD_LP

Variables	*HQD_LP (1)*	*HQD_LP (2)*	Variables	*HQD_LP (1)*	*HQD_LP (2)*
SCD	0.312***(0.064)	0.148**(0.060)	$Duality$		-0.005(0.007)
$Size$		0.254***(0.009)	$Indep$		−0.145**(0.067)
Age		0.259***(0.040)	$Top10$		0.211***(0.038)
Lev		0.487***(0.031)	$Firm/Year$	Yes	Yes
Roa		2.359***(0.075)	$Samples$	21321	21321
$Growth$		0.239***(0.012)	$constant$	14.161*** (0.002)	11.106***(0.135)
$Intang$		−1.061***(0.139)	Adj_R^2	0.859	0.903
$Cashflow$		0.035(0.026)			

Note: * * * indicates p < 0.01, * * indicates p < 0.05, * indicates p < 0.10, and values in parentheses indicate robust standard errors.

4.3 Robustness Checks

4.3.1 Propensity score matching (PSM) model

To address the issue of endogeneity potentially arising from sample self-selection, this study employed PSM as a testing method. The full sample of firms was divided into two groups based on whether SCD was implemented. Firm size, age, financial leverage, profitability, growth rate, intangible asset ratio, independent director ratio, and equity concentration were included as covariates. Nearest-neighbor matching with a 1:4 ratio was adopted as the matching strategy, and a control group sharing comparable characteristics was selected for the treatment group. As shown in column (1) of Table 3, the average treatment effect on the treated (ATT) for SCD firms is both statistically significant and positive at the 1% significance level. The SCD coefficient in the model remains significant and positive, further confirming the robustness of the results.

4.3.2 IV-2SLS model

To mitigate potential endogeneity issues caused by omitted variables or reverse causality, internet access per 10,000 people was adopted as an instrumental variable (SCD_IV) and a two-stage least squares (2SLS) regression was employed in this study. This instrument captures the regional digital infrastructure level, which is closely associated with SCD but is unlikely to directly affect other factors influencing supply chain outcomes, thus satisfying the conditions for instrument relevance and validity. According to the regression diagnostics, the Kleibergen-Paap rk LM statistic is 26.278, exceeding the critical value of 16.380 and showing significance at the 1% level. This confirms the strength of the instrument and rules out concerns of weak identification. Regression results reported in columns (2) and (3) of Table 3 further support this. First, SCD_IV shows a significantly positive correlation at the 1% level, indicating that regional internet accessibility is a strong driver of SCD development. Second, the SCD coefficient remains significantly positive, which reinforces the robustness of the empirical results.

Table 3. PSM matching and IV-2SLS regression results

Variables	Nearest Neighbor Matching (1)	1st Stage (2) *SCD*	2nd Stage (3) *HQD_LP*
$SCDIV$		0.001^{***} (0.000)	
SCD	$0.214^{***}(0.069)$		$5.993^{***}(1.925)$
$Controls$	Yes	Yes	Yes
$Firm/Year$	Yes	Yes	Yes
$Samples$	17948	21321	21321
$constant$	$11.128^{***}(0.146)$	-0.010(0.015)	$9.690^{***}(0.208)$
Adj_R^2	0.898		
ATT	Difference $= 0.111^{***}$; T $= 7.540$		

Note: * * * indicates p $<$ 0.01, * * indicates p $<$ 0.05, * indicates p $<$ 0.10, and values in parentheses indicate robust standard errors.

4.3.3 Alternative tests for SCD

To verify the robustness of the conclusions, SCD was assessed through principal component analysis (PCA) as an alternative to the original TF-IDF measure. Based on SPSS26.0, the KMO value of the sample data is 0.589 ($>$0.500) and Bartlett's Sphericity result is 0.000, showing that the above indicators are suitable for PCA. Considering the eigenvalues, factor correlation, and cumulative explanatory variables, the number of extracted factors was set to 3, and the cumulative variance contribution rate of the first three factors reached 83.860% ($>$60%); these extracted factors can represent most of the information contained in the digitized raw data of the supply chain of the research sample. According to the regression outcome in Table 3, column (1), the SCD coefficient is significantly positive at the 1% threshold, reinforcing the reliability of the study's conclusions.

4.3.4 Alternative validation using high-quality manufacturing development indicators

The OP approach and a composite evaluation indicator system were employed to measure the high-quality development level of manufacturing firms. Following the study by Liu and He [52], the composite system incorporated 15 secondary indicators across five dimensions—technological innovation, green development, openness, economic efficiency, and industrial coordination (e.g., R and D intensity, energy consumption per unit of value added, trade openness, manufacturing growth rate, and the share of manufacturing output). The entropy method was used to calculate a weighted composite score representing the level of high-quality development at the provincial level. This provincial-level indicator was then mapped to the firm level based on each firm's location, serving as a proxy variable for firm-level high-quality development (HQD_Mhq). Observations from 13 firms located in Tibet were excluded from the dataset. Control variables at the macro level include regional economic development ($LnPGDP$, the natural logarithm of per capita GDP), the degree of government intervention (GOV, calculated as general fiscal expenditure divided by GDP), and infrastructure density ($ITND$, measured by the ratio of total road and railway mileage to administrative area). In addition, the data for the macro-level measurement indicators were obtained from the CNRDS database. Regression outcomes in Table 4, columns (2) and (3), reveal that the SCD coefficient is significantly positive at the 5% and 1% thresholds, confirming the reliability of the results.

Table 4. Robustness test results for the replacement variables

Variables	*HQD_LP* (1)	*HQD_OP* (2)	*HQD_Mhq* (3)
SCD	$0.119^{***}(0.046)$	$0.144^{**}(0.059)$	$0.027^{***}(0.008)$
$Controls$	Yes	Yes	Yes
$Firm/Year$	Yes	Yes	Yes
$Samples$	21321	21321	21216
$Constant$	$11.105^{***}(0.135)$	$12.783^{***}(0.138)$	$2.753^{***}(0.083)$
Adj_R^2	0.903	0.873	0.963

Note: * * * indicates p $<$ 0.01, * * indicates p $<$ 0.05, * indicates p $<$ 0.10, and values in parentheses indicate robust standard errors.

5 Extension Analysis

5.1 Mediation Mechanism Test

Previous studies have shown that SCD can enhance high-quality manufacturing development, but the specific transmission mechanisms remain unclear. Based on the theoretical analysis in this study, SCD may indirectly promote high-quality manufacturing development by facilitating supply chain collaborative innovation and advancing SCF.

Moreover, environmental dynamism is expected to enhance the link between SCD and both supply chain collaborative innovation and SCF. Following the study by Ting [53], the test model was developed as follows:

$$M_{it} = \beta_0 + \beta_1 SCD_{it} + \beta_2 X_{it} + u_i + \delta_t + \varepsilon_{it} \tag{6}$$

where, M represents the mediating variables, specifically supply chain collaborative innovation ($CInnov$) and SCF; the other variables are consistent with the definitions in Eq. (5). If the coefficient β_1 in Eq. (6) is significantly positive, it provides empirical support for Hypotheses 2 and 3. Additionally, Eqs. (7) and (8) were constructed to examine whether environmental dynamism (EN) positively moderates the digitalization-induced transmission paths of SCD. If the coefficients φ_3 and ρ_3 are significantly positive, they indicate that Hypotheses 4 and 5 are valid.

$$HQD\_LP_{it} = \varphi_0 + \varphi_1 SCD_{it} + \varphi_2 EN_{it} + \varphi_3 SCD_{it} \times EN_{it} + \varphi_4 Clnnov_{it} + \varphi_5 X_{it} + u_i + \delta_t + \varepsilon_{it} \tag{7}$$

$$HQD\_LP_{it} = \rho_0 + \rho_1 SCD_{it} + \rho_2 EN_{it} + \rho_3 SCD_{it} \times EN_{it} + \rho_4 SCF_{it} + \rho_5 X_{it} + u_i + \delta_t + \varepsilon_{it} \tag{8}$$

5.1.1 Facilitating the supply chain collaborative innovation mechanism

$CInnov$ was evaluated using the natural logarithm of one plus the total number of patents jointly obtained by manufacturing firms and other external entities. The corresponding patent data were obtained from the CNRDS database and further screened to include only patents jointly filed by the listed companies themselves (excluding subsidiaries, associates, joint ventures, and group firms) and external partners. The dataset includes invention, utility model, and design patents; and the cumulative count was logged after adding one to serve as a proxy for firms' collaborative innovation activity within the supply chain. A greater $CInnov$ value reflects stronger engagement in cross-organizational innovation activities. According to the estimation in column (1) in Table 5, the coefficient of SCD is significantly positive at the 1% level, suggesting that SCD fosters high-quality manufacturing development by promoting $CInnov$. Hypothesis 2 is supported. This result highlights the enabling role of SCD in breaking organizational boundaries and enhancing trust, resource integration, and knowledge sharing across the supply chain. From an economic perspective, digital infrastructure facilitates more agile and cost-effective coordination of joint R and D activities, reducing duplication and accelerating innovation cycles. For managers, this implies that investments in digital supply chain platforms—such as cloud-based collaboration tools, real-time data interfaces, or digital twins—can serve as strategic levers to enhance cross-enterprise innovation capacity. Practically, manufacturing firms should foster closer data and technology sharing mechanisms with upstream and downstream partners, thereby unlocking greater value through synergistic innovation.

5.1.2 Promoting the SCF development mechanism

Building on the study by Gu et al. [41], SCF was set as a binary indicator and the search condition was defined as the firm name plus terms including SCF, supply chain management, and other related keywords. Subsequently, through the Baidu search and content-based text analysis, whether the company carries out SCF business for firms in the chain was determined; if it does, the value of SCF is 1; otherwise, it is 0. According to column (2) in Table 5, SCD exhibits a statistically significant positive coefficient at the 5% level, suggesting that SCD helps advance high-quality manufacturing development by facilitating SCF expansion across firms in the supply chain. Hypothesis 3 is supported. This finding reflects the role of SCD in improving financial transparency and information symmetry across the supply chain, thereby strengthening the effectiveness of SCF tools. Digitalization enhances firms' ability to monitor transactions, evaluate credit, and coordinate financing flows in real time. For managers, investing in supply chain digital infrastructure can help unlock embedded financial value, improve capital turnover, and mitigate financing constraints, particularly for SMEs.

5.1.3 Analyzing the influence of environmental dynamism as a moderator

Building on the study by Wang et al. [54], EN is measured as the ratio of the standard deviation of a firm's sales revenue in the past five years to its five-year average. A larger ratio indicates a higher degree of EN faced by the firm. The estimation results, reported in columns (3) and (4) in Table 5, show that φ_3 and ρ_3 exhibit significant positive effects at the 5% threshold, suggesting that EN positively moderates the mediating mechanisms through which SCD influences manufacturing firms' high-quality development. Therefore, Hypotheses 4 and 5 are supported. This finding highlights that SCD's effectiveness in promoting collaborative innovation and SCF is amplified in more dynamic environments. Greater environmental volatility increases firms' reliance on timely information, agile coordination, and real-time financing support. In such contexts, SCD serves as a strategic enabler of adaptability and responsiveness. Managers operating under uncertainty should prioritize investments in digital infrastructure to strengthen supply chain visibility, coordination, and financial resilience.

Table 5. Mechanism test results

Variables	*CInnov* (1)	*SCF* (2)	*HQD_LP* (3)	*HQD_LP* (4)
SCD	$0.690^{***}(0.154)$	$0.155^{**}(0.068)$	0.084(0.068)	0.105(0.067)
$CInnov$			$0.027^{***}(0.003)$	
SCF				$0.038^{***}(0.007)$
EN			$0.308^{***}(0.029)$	0.308^{***} 0.028)
$SCD \times EN$			0.666^{**} (0.277)	$0.609^{**}(0.278)$
$Controls$	Yes	Yes	Yes	Yes
$Firm/Year$	Yes	Yes	Yes	Yes
$Samples$	21321	21321	14948	14948
$Constant$	$-1.266^{***}(0.308)$	0.030(0.136)	$11.122^{***}(0.193)$	$11.067^{***}(0.194)$
Adj_R^2	0.649	0.411	0.906	0.905

Note: * * * indicates p < 0.01, * * indicates p < 0.05, * indicates p < 0.10, and values in parentheses indicate robust standard errors.

5.2 Heterogeneity Analysis

5.2.1 Considering corporate ownership characteristics

The sample was classified into state-owned firms (SOEs) and non-state-owned firms (non-SOEs) according to firm ownership types. The regression results, as illustrated in columns (1) and (2) in Table 6, reveal that SCD has a significantly positive effect on the high-quality development of non-SOEs at the 1% level, whereas its effect on SOEs is not statistically significant. One reason is that non-SOEs may face greater pressure in market competition, making them more inclined to adopt new technologies and digitalization tools. In contrast, SOEs may lack sufficient incentives to pursue innovation and efficiency due to policy protection, market monopoly status, or other non-market factors. In addition, SOEs may be more cautious about adopting technologies and business models that may bring uncertainty.

Table 6. Heterogeneity analysis

Variables	SOEs (1)	Non-SOEs (2)	Growth (3)	Maturity (4)	Decline (5)	HRRG (6)	LRRG (7)
SCD	-0.060 (0.143)	0.191*** (0.065)	0.146* (0.087)	0.074 (0.111)	0.460*** (0.176)	0.179 (0.170)	0.171** (0.071)
$Controls$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Firm/Year$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Samples$	6442	14879	9308	7390	3029	5959	14932
$Constant$	11.110*** (0.263)	11.164*** (0.160)	11.112*** (0.172)	11.404*** (0.230)	11.551*** (0.619)	11.173*** (0.291)	11.133*** (0.173)
Adj_R^2	0.909	0.887	0.902	0.927	0.877	0.891	0.903

Note: * * * indicates p < 0.01, * * indicates p < 0.05, * indicates p < 0.10, and values in parentheses indicate robust standard errors.

5.2.2 Considering the corporate lifecycle

Drawing on the study by Dickinson [55], the firm lifecycle was segmented into three stages—growth, maturity, and decline—based on the cash flow portfolio method. In columns (3) to (5) in Table 6, the results show that SCD positively contributes to high-quality manufacturing development in both the growth and decline periods; the latter (1%) has a more pronounced effect than the former (10%). Firms in the growth stage tend to adopt new technologies and management practices more readily to boost innovation and R and D, improving their resilience to risks. In contrast, firms in the decline period facing problems of declining market share and operational efficiency are more eager to integrate resources through SCD to transform and revitalize. By contrast, SCD fails to exhibit a statistically meaningful effect on the high-quality development of mature firms, possibly due to their already optimized supply chain management or organizational inertia that hinders digital transformation initiatives.

5.2.3 Considering corporate resource redundancy

Following the study by Chen et al. [56], resource redundancy was measured using the current ratio, dividing the sample into a high resource redundancy group (HRRG, greater than the mean) and a low resource redundancy group (LRRG, less than the mean). In Table 6, columns (6) and (7) show that SCD significantly enhances high-quality development at the 5% level among firms in LRRG, while it is not significant in HRRG. The implication is that firms with fewer resources may prioritize resource allocation efficiency or face considerable competitive pressures, incentivizing them to adopt SCD's technological or resource advantages to optimize their operational efficiency and competitiveness. In contrast, firms with high resource redundancy may have sufficient buffer resources to cope with supply chain uncertainties and risks. Moreover, resource abundance may cause organizational inertia, making them more cautious about SCD's transformational changes and technological innovations.

5.3 Analysis of Economic Consequences

The analyses in Sections 4–5 confirm that SCD can improve high-quality development of manufacturing firms. However, can SCD facilitate the stable development of firms' long-term value? Exploring this question deepens the understanding of the economic consequences of SCD in driving high-quality manufacturing development and validates its effectiveness in promoting long-term sustainable development.

A firms' accounting return was combined with market performance indicators to measure their long-term value ($Value$). This measure considers both the firm's current operating conditions and investor expectations regarding market prospects. The calculation is as follows: $Value = \left(ROE' + TobinQ)'\right)/2$, where ROE represents return on equity, $TobinQ$ represents the proportion of market value to asset replacement cost, and ROE' and $TobinQ'$ denote standardized values of ROE and $TobinQ$, respectively. This study further employed a one-period lag of the long-term value indicator in regression analysis. According to the regression output in column (1) in Table 7, SCD shows a significantly positive coefficient at the 10% level, indicating its role in enhancing the long-term value of manufacturing firms. Column (2) includes the high-quality development variable (HQD_LP) in the model, and the estimation results reveal that SCD's positive impact on long-term value is realized through improved high-quality development, with statistical significance at the 1% level. Nonetheless, the coefficient of SCD in column (2) is smaller than that in column (1), supporting the view that high-quality development serves as a full mediator. These findings reinforce the conclusion that SCD not only boosts high-quality development but also promotes the long-term value of manufacturing firms. For firm-level decision-makers, this highlights the importance of viewing SCD as a long-term strategic investment rather than a short-term cost-reduction tool. Integrating digital initiatives with high-quality development strategies can enhance firm resilience, market valuation, and stakeholder confidence in dynamic business environments.

Table 7. Results of the analysis of economic consequences

Variables	***Value_Long*** **(1)**	***Value_Long*** **(2)**
SCD	0.008*(0.004)	0.007(0.004)
HQD_LP		0.006***(0.001)
$Controls$	Yes	Yes
$Firm/Year$	Yes	Yes
$Samples$	18636	18636
$Constant$	0.302***(0.008)	0.235***(0.010)
Adj_R^2	0.527	0.533

Note: * * * indicates p < 0.01, * * indicates p < 0.05, * indicates p < 0.10, and values in parentheses indicate robust standard errors.

6 Discussion and Conclusion

6.1 Main Findings

With the promotion of national policies and support of digital technology, SCD has contributed to accelerating industrial revitalization and boosting real economic recovery. Taking A-share manufacturing firms listed in Shanghai and Shenzhen during 2008–2022 as the data source, this study conducted an empirical investigation into the influence of SCD on high-quality development of manufacturing firms, along with its underlying mechanisms and economic effects, with a particular focus on supply chain integration.

The findings show that SCD can effectively promote high-quality manufacturing development, which aligns with empirical evidence [8, 11, 22],demonstrating SCD's positive influence on firm outcomes. However, unlike existing research, this study adopted a multi-factor approach using both LP and OP methods to explore the mechanisms by which SCD promotes high-quality development in manufacturing [18].

The main conclusions drawn from this study are unlike those of previous studies. First, the multi-factor analysis shows that SCD plays a significant role in promoting high-quality development of manufacturing firms through collaborative innovation and SCF within the framework of high environmental dynamism. Second, SCD can further sustain the long-term value development of manufacturing firms by improving their development quality. Finally, SCD's effect on high-quality manufacturing development is particularly notable among non-SOEs, as well as firms in the growth or decline phases and those with limited resource buffers.

6.2 Theoretical Implications

From a theoretical perspective, this study makes three key contributions to the literature on SCD and the high-quality development of manufacturing firms.

First, this study constructed an integrated analytical framework that simultaneously draws on dynamic capability theory, resource-based theory, financial intermediation theory, and organizational adaptation theory. By doing so, it provides a more comprehensive theoretical lens to explain how SCD enhances firms' responsiveness, resource integration, financial efficiency, and adaptive capacity in dynamic environments, thereby enabling high-quality development in the manufacturing sector.

Second, while prior research has primarily examined the role of SCD from operational or efficiency-oriented perspectives [4], this study deepens the theoretical understanding by identifying two key mediating mechanisms—supply chain collaborative innovation and SCF. These mechanisms elucidate the strategic, innovation-driven, and financial pathways through which SCD translates into long-term value creation, offering a more holistic explanation of the value-enhancing role of SCD in manufacturing.

Third, the study introduced environmental dynamism as a boundary condition that moderates the effectiveness of the above mediating mechanisms. It demonstrates that higher environmental uncertainty reinforces the positive effects of both collaborative innovation and SCF, thus enriching the contextual understanding of how and when SCD contributes to the high-quality development of manufacturing firms. Moreover, by endogenizing environmental dynamism into the analytical framework, the study advanced the theoretical boundary of SCD research from static efficiency enhancement to dynamic adaptability in uncertain environments.

Collectively, these contributions go beyond confirming that SCD promotes high-quality development; they also explain how such effects materialize through innovation and financial mechanisms, and under what conditions they are most pronounced. In doing so, this study not only enriches the theoretical discourse on SCD but also provides a new theoretical basis for promoting sustainable and high-quality transformation in the manufacturing industry under conditions of environmental uncertainty.

6.3 Managerial Implications

Based on the findings, the following management recommendations were proposed: First, government authorities in China are advised to intensify their efforts in supporting the digital upgrading of SMEs and non-SOEs, while also enhancing the transformation momentum of state-owned and large-scale firms. It was found in this research that non-SOEs, firms in the growth and decline stages, and those with low resource redundancy exhibit more significant supply chain digital transformation. However, they also face substantial challenges. The government departments should provide guidance on digital transformation, technical support, financial subsidies, and tax incentives to facilitate their upgrades in supply chain management. Additionally, for firms with high resource redundancy, large firms, SOEs, and firms in the maturity stage, the government departments should optimize management structures, enhance innovation capabilities, strengthen collaboration with technology innovation entities, and implement customized digitalization strategies.

Second, the government and related departments should advance the digital integration of supply chain participants, including upstream and downstream firms, by establishing cross-industry collaborative platforms. These platforms should facilitate data exchange and collaboration between firms and financial institutions. For example, the manufacturer can implement blockchain technology to improve data security by optimizing inventory management and demand forecasting, using technologies such as big data and AI, enabling the firms to have more accurate and efficient decision support. Additionally, financial institutions can develop supply chain financial products and services to improve transparency and streamline supply chain operations, including the launch of Shunfeng Digital's "Warehouse Financing" by CCB Shenzhen, and the first enterprise data asset pledge financing by Bank of Jiangxi.

Third, relevant administrative departments should optimize digital infrastructure construction and foster policies conducive to innovation. They should strive to build a flexible, open digital ecosystem capable of rapidly adapting to market changes by systematically investing in high-speed broadband networks and advanced digital technologies, ensuring that firms can make timely business decisions.

6.4 Limitations and Future Directions

While this study offers valuable contributions in both theoretical and practical contexts, there remain areas for future investigation to address its limitations. First, the research sample could be expanded to include listed firms across a broader range of industries in China, allowing for a more comprehensive view of the challenges and potential of SCD in promoting high-quality development of manufacturing and other firms. Second, in the present study, the dictionary construction for the text analysis of the SCD indicator may be incomplete; future research could combine the big language model Word2Vec and machine learning to measure the impact of other variables, such as investment efficiency and capacity utilization.

Author Contributions

Methodology, H.H.L.; formal analysis, Z.F.Y.; investigation, Z.F.Y.; writing—original draft preparation, Z.F.Y.; writing—review and editing, H.H.L.; visualization, Z.F.Y.; supervision, H.H.L. All authors have read and agreed to the published version of the manuscript.

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Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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